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The Diversity-Bandwidth Trade-off[1]

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The authors propose that a trade-off between network diversity and communications bandwidth regulates access to novel information because a more diverse network structure increases novelty at a cost of reducing information flow. Received novelty then depends on whether (*a*) the information overlap is small enough, (*b*) alters' topical knowledge is shallow enough, and (*c*) alters' knowledge stocks refresh slowly enough to justify bridging structural holes. Social network and e-mail content from an executive recruiting firm show that bridging ties can actually offer less novelty for these reasons, suggesting that the strength of weak ties and structural holes depend on brokers' information environments.

Where does one find novel information? Most modern sociological theory suggests that we find novelty through weak ties that span structural holes. A more precise question, however, is where does one find the most novel

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information per unit of time? That is, at what rate do we receive novelty from our different social contacts? We should get information with greater novelty from across a structural hole but at a slower rate because interactions with bridging ties are weaker, are less frequent, and have lower bandwidth. Although we should get information with less novelty from a cohesive tie, we should receive novelty at a faster rate because the tie is stronger, the interaction more frequent, and the bandwidth higher. Contrary to conventional wisdom, this stronger tie can in certain circumstances provide greater total novelty over time. Since strong high-bandwidth ties are more likely in cohesive networks and weak low-bandwidth ties more likely in sparse networks, the two factors affecting the rate at which we find novel information—structural diversity and channel bandwidth—trade off, creating countervailing effects on access to novel information. We develop a theory of this trade-off and the contingencies of social structure and information environments that affect access to novelty. We test this theory on observed information content flowing through organizational e-mail networks. Results suggest that information benefits to brokerage depend on the information environments in which brokers find themselves and that we should embrace a more nuanced view of how information flows in social networks.

THE DIVERSITY-BANDWIDTH TRADE-OFF

The assumption that network structure influences the distribution of information and knowledge in social groups (and thus characteristics of the information to which individuals have access) underpins a significant amount of theory linking social structure to outcomes such as wages, job placement, promotion, creativity, innovation, political success, social support, productivity, and performance (Simmel [1922] 1955; Moreno, Jennings, and Sargent 1940; Granovetter 1973; Baker 1990; Burt 1992, 2004; Padgett and Ansell 1993; Uzzi 1996, 1997; Hansen 1999, 2002; Podolny 2001; Reagans and Zuckerman 2001; Van Alstyne and Bulkley 2004; Aral, Brynjolfsson, and Van Alstyne 2007*a*, 2007*b*). The central argument in this body of theory is that structurally diverse networks—networks low in cohesion and structural equivalence and rich in structural holes—provide access to diverse, novel information. Contacts maintained through weak ties are typically unconnected to other contacts and therefore more likely to "move in circles different from our own and thus [to] have access to information different from that which we receive" (Granovetter 1973, p. 1371). These ties are "the channels through which ideas, influence, or information socially distant from ego may reach him" (p. 1371). As Burt (1992, p. 16) argues, "everything else constant, a large, diverse network

is the best guarantee of having a contact present where useful information is aired." Since information in local network neighborhoods tends to be redundant, structurally diverse contacts that reach across structural holes should provide channels through which novel information flows (Burt 1992).

Novel information is thought to be valuable because of its local scarcity. Actors with scarce information in a given network neighborhood are better positioned to broker opportunities, make better decisions, and apply information to problems that are intractable given local knowledge (e.g., Hargadon and Sutton 1997; Reagans and Zuckerman 2001; Burt 2004; Rodan and Gallunic 2004; Van Alstyne and Brynjolfsson 2005; Lazer and Friedman 2007). Access to novel information should increase the breadth of individuals' absorptive capacity, strengthen the ability to communicate ideas across a broader range of topics to a broader audience, and improve persuasion and the ability to generate broader support from subject matter experts (Cohen and Levinthal 1990; Simon 1991; Reagans and McEvily 2003; Rodan and Galunic 2004). For these reasons, networks rich in structural diversity are thought to confer "information benefits" or "vision advantages" that improve performance by providing access to diverse and novel perspectives, ideas, and information (Burt 1992).

These are the central inferences on which structural theories of brokerage and the strength of weak ties rest, and it is therefore intuitive to expect that *having structurally diverse networks—networks low in cohesion and structural equivalence and rich in structural holes—is positively associated with receiving more diverse information and more total nonredundant information* and that *access to more diverse information and more total nonredundant information is positively associated with individual performance.*[2] Over the last four decades, these two inferences have guided the way sociologists think about information flow in networks, motivating and informing thousands of empirical studies of in-

[2] We define the "structural diversity" or "network diversity" of an ego network as the extent to which it is low in "constraint" as defined by Burt (1992, p. 55), low in the average structural equivalence of alters, and rich in structural holes. We define the "structural cohesion" or "network cohesion" of an ego network as the extent to which it is high in "constraint" as defined by Burt, low in structural holes, and high in the average structural equivalence of alters. Various phrases have been used in the literature to describe analogous concepts including ego density (or sparseness) and network embeddedness. These definitions and their measures are highly correlated with and change in proportion to network diversity and network cohesion. We chose to use the phrases "network diversity" and "network cohesion" because they are the ones most commonly used in the literatures to which we refer (e.g., Burt 1992, 2004, 2005; Reagans and McEvily 2003). At times we also use the terms "embeddedness" and "constraint" to highlight that our arguments draw from and contribute to literatures that also use those terms (e.g., Granovetter 1985; Burt 1992; Uzzi 1996, 1997).

novation (Hargadon and Sutton 1997; Burt 2004), academic output (Swedberg 1990), team performance (Reagans and Zuckerman 2001), the formation of industry structures (Walker, Kogut, and Shan 1997), the success of social movements (Centola and Macy 2007), and labor market outcomes (Montgomery 1991).

However, theoretical arguments linking network diversity to novel information have thus far focused almost exclusively on the relative diversity of the information received across different alters in a network, generally overlooking the diversity and volume of novel information flowing within each tie or channel over time. Although dense, cohesive networks tend to deliver information that is redundant across channels (with each alter providing the same or similar information), relationships in such networks are also typically stronger (Granovetter 1973; Burt 1992), implying greater frequency of interaction and richer information flows. Metaphorically, such ties have greater channel bandwidth. In contrast, weak ties offer less communication (Granovetter 1973; Burt 1992), and information should flow through them less frequently (Granovetter 1973), with lower complexity and detail (Uzzi 1997; Hansen 1999).[3]

Two mechanisms explain why socially distant weak ties should interact and communicate less: exposure and motivation. As contacts interact more frequently, they are more likely to be exposed to and to spend time with each others' contacts in cohesive embedded networks (Granovetter 1973). Cohesive embedded networks also motivate their members to interact with one another: social pressure, cognitive balance, and the development of cooperative norms in embedded relationships inspire us to devote time and energy to communicating with embedded ties (Heider 1958; Newcomb 1961; Granovetter 1973, 1985, 1992; Coleman 1988).[4] In relationships

[3] We use the phrase relationship "channel bandwidth" carefully and in preference to the more inclusive "strong tie" to draw attention to the volume of literal communication shared among people. In general, stronger ties imply greater bandwidth, but the added precision allows us to also handle unusual cases. For example, individuals may have strong ties to parents based on emotional affinity, trust, or caregiving yet be observed to communicate more frequently with coworkers who are less emotionally significant in their lives. We draw out the importance of focusing on information diversity and volume, observed over actual communications channels, in developing the theories that follow. The strength of a tie may be a noisy reflection of the bandwidth of the channel. More detailed empirical work on the relationship between the strength of ties and the bandwidth of channels may provide evidence on how the social function of relationships (Podolny and Barron 1997; Burt 2000) is associated with the nature of the conduits of information flow they enable. We encourage this work, although we do not focus on it here.

[4] As Granovetter (1973, p. 1362) notes, homophily could also explain closure without a causal relationship between the strength of ties and closure, breaking the causal relationship between structural diversity and the rate and volume of interaction (if individuals interact more with similar others because they are similar and not because

among firms in New York's apparel industry, for example, Uzzi (1997) reports that socially distant weak ties were "non-repeated . . . one shot deals" in which communication occurred much less frequently, whereas embedded ties were characterized by "constant communication." Similar evidence has been found in research and development (R&D) organizations (Allen 1977; Reagans and Zuckerman 2001; Reagans and McEvily 2003), innovation labs (Hargadon and Sutton 1997), job seeking (Granovetter 1973), familial relations (Coleman 1988), and relationships between firms' business units (Hansen 1999) and across firms (Helper, MacDuffie, and Sabel 2000). Given evidence suggesting the prevalence of weak ties in structurally diverse networks and the likelihood of increased information flow in cohesive networks due to motivation and exposure, the bandwidth of communication channels should be lower in diverse networks. Thus, network diversity and channel bandwidth should trade off such that *greater network diversity is associated with lower channel bandwidth* (see fig. 1).

All else equal, greater channel bandwidth should also provide access to more diverse information and more total nonredundant information because interaction through rich high-bandwidth channels tends to be more detailed, cover more topics, and address more complex, interdependent concepts. While unconnected alters may have more novel information, the amount of useful novel information delivered to ego should increase in cohesive networks, in which both the volume of the information flow and the motivation to share relevant novel information are greater. As Reagans and McEvily (2003, p. 262) argue, "It is easier to transfer all kinds of knowledge [codified and tacit, simple and complex] in a strong tie and more difficult to transfer all kinds . . . in a weak tie." If many interdependent ideas must be applied together, then throughput must increase to transfer them all. Even the seminal work favoring weak ties as a source of novel information foreshadows in a footnote that "one possible model would expect information to flow through ties in proportion to time expended in interaction; this model would predict much more information via strong ties" (Granovetter 1973, p. 1372). We consider how just such a model can reform conventional wisdom regarding the relationship between social structure and access to novel information.

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they are connected in embedded relationships). However, prior empirical work on friendship formation demonstrates that exposure and preferences both play highly significant roles in tie formation (see Currarini, Jackson, and Pin 2009, 2010). The diversity-bandwidth trade-off can therefore be viewed to a significant extent as a causal theory, with structure driving the rate and volume of interaction. Exposure and motivation are likely to play an even bigger role in our setting because we study work relationships in which, as we explain in our empirical analyses, recruiters seek diversity constrained by exposure in order to perform well at work.

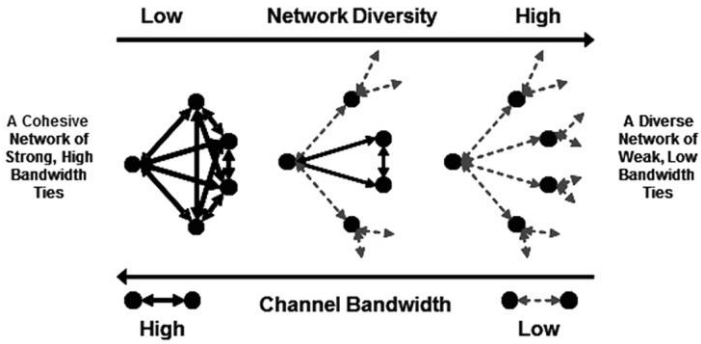


FIG. 1.—The diversity-bandwidth trade-off. As structural diversity increases, channel bandwidth decreases.

SOCIAL PROCESSES AND ACCESS TO NOVEL INFORMATION

While most current theories describe networks as channels, pipes, bridges, or conduits (e.g., Podolny 2001; Centola and Macy 2007), characterize content as "attributes of nodes" (e.g., Rodan and Galunic 2004), and implicitly assume that information flows in proportion to the distribution of information in the network (e.g., Granovetter 1978; Schelling 1978; Kempe, Kleinberg, and Tardos 2003),[5] information exchange is fundamentally a social process and knowledge transfer a discretionary activity (Reagans and McEvily 2003; Wu et al. 2004). A connection to any individual affords the possibility of receiving the information she possesses but by no means guarantees it. As Wu et al. point out, "information is selective and passed by its host only to individuals the host thinks would be interested in it" (2004, p. 328). In competitive settings, information is often withheld even when it is known to be of interest to others. Networks are not simply pipes into different pools of information; they reflect the nature of the relationships, interactions, and information exchanges taking place among those they connect.

Although the channel, pipe, bridge, and conduit metaphors are common

[5] Two core models have emerged to explain the diffusion of influence and contagion. Threshold models posit that individuals adopt innovations (or receive information) after surpassing their own private "threshold" (e.g., Granovetter 1978; Schelling 1978). Cascade models posit that each time an adjacent individual adopts, the focal actor adopts with some probability that is a function of their relationship (e.g., Kempe et al. 2003). While both models assume information transmission between adopters and nonadopters, they rarely specify the nature of the information or the conditions under which exchanges take place. Rather, the diffusion process is typically tested under various assumptions about the distribution of thresholds or dyadic adoption probabilities in the population. In fact, as Kempe et al. explain, "The fact that [thresholds] are randomly selected is intended to model our lack of knowledge of their values" (2003, p. 2).

in sociology, such terminology hides restrictive assumptions about network structure preceding information flow. Human interactions in fact define social network structure. So, to avoid problems with channel metaphors, we argue first from social processes, using social distance as synecdoche for less frequent interaction, lower mutual commitment, and limited understanding. Speaking metaphorically, social distance is inverse bandwidth. Five social mechanisms, summarized in table 1, then explain why greater channel bandwidth and lower social distance should *increase* access to novel information.

Social capital.—In relationships characterized by strong cohesive ties, contacts are likely to be more willing to share information. Diverse, low-bandwidth ties are typically opportunistic, functional, and only selfishly cooperative (Granovetter 1973; Uzzi 1997), whereas cohesive, embedded ties are typically characterized by greater intimacy, trust, emotional intensity, and mutual confiding (Coleman 1988; Uzzi 1996). Social cohesion motivates individuals to devote time and effort to communicating with and assisting one another (Granovetter 1985; Coleman 1988). The development of cooperative norms (Granovetter 1992) and the subsequent reduction in competition in cohesive networks are likely to increase knowledge transfer between individuals (Szulanski 1996; Argote 1999; Reagans and McEvily 2003). Social capital in strong high-bandwidth relationships gives ego the standing to seek information and alter the comfort to offer information. It also engenders the levels of trust that allow contacts to share both sensitive and nonsensitive information. A weak-tie relationship will typically provide access to only the nonsensitive information. Similarly, in weak-tie relationships, alters will be less willing to devote time and effort to information exchanges with ego, who will get less in return for placing burdensome requests and will receive less total novel information.

In the context of job seeking, Granovetter (1973, p. 1371) nicely sets up the open empirical question we seek to address: "A natural a priori idea is that those with whom one has strong ties are motivated to help with job information. Opposed to this greater motivation are the structural arguments I have been making: those to whom we are weakly tied . . . will have access to information different from that which we receive." Social capital, developed through prior information sharing, enables ego to seek and encourages alters to share more novel information in high-bandwidth relationships. Indeed, a weak-tie alter is likely to have already pushed such valuable information to his or her own strong ties before honoring weak-tie requests from ego. Whether strong or weak ties deliver more total novel information therefore remains a critical open question.

Transactive memory.—Wegner (1987) introduced the term "transactive memory" to describe intimate relationships in which individuals have

TABLE 1
IMPLICATIONS OF THE DIVERSITY-BANDWIDTH TRADE-OFF FOR ACCESS TO NOVEL INFORMATION

Theory	Ego's Perspective	Alter's Perspective
Social capital (e.g., Putnam 1995; Burt 1992; Tsai and Ghoshal 1998; Lin 2002)	Greater intimacy, trust, reciprocity, and cooperation in cohesive-high-bandwidth networks makes ego more willing to request novel information from alter	Greater intimacy, trust, reciprocity, and cooperation in cohesive-high-bandwidth networks make alter more willing to share novel information with ego
Transactive memory (e.g., Wegner 1987; Liang et al. 1995)	Awareness of whom to ask and what to ask for in cohesive-high-bandwidth networks enables ego to request novel information more effectively from alter	Awareness of what to volunteer in cohesive-high-bandwidth networks enables alter to volunteer relevant novel information more effectively to ego
Search transfer (e.g., Hansen 1999)	Close, frequent interaction and tight coupling in cohesive-high-bandwidth networks makes ego better able to comprehend and thus receive novel information from alter	Close, frequent interaction and tight coupling in cohesive-high-bandwidth networks make alter able to express and thus transfer novel information to ego
Knowledge creation (e.g., Uzzi 1996, 1997; Obstfeld 2005; Uzzi and Spiro 2005)	Embeddedness and cohesion enable ego to find synergies and connections between her information and alter's information in order to generate new ideas and new novel information	Embeddedness and cohesion enable alter to find synergies and connections between her information and ego's information in order to generate new ideas and new novel information
Homophily (e.g., Blau 1986; Uzzi 1997; Helper et al. 2000; McPherson et al. 2001)	Alters are more likely to have mutual interests with ego across a wider variety of topics inspiring multifaceted communication and access to more of the different dimensions of alters' information	Ego is more likely to have mutual interests with alters across a wider variety of topics inspiring alter to communicate more of the different dimensions of their information

organized into mutually determined and understood domains of expertise. Although developing a relationship can be understood "as a process of mutual . . . disclosure . . . it can also be [understood] as a necessary precursor to transactive memory" (1987, p. 200). As relationships develop, contacts become more familiar with each other's areas of interest and expertise. Knowing who knows what makes embedded relationships with high-bandwidth communication channels a more likely source of novel information.

Discovery of remote information is more likely when ego knows whom to ask for it (Wegner 1987). Stronger ties are more familiar with each other's catalog of knowledge, inspiring information exchanges on a larger number and wider variety of topics. The greater the social distance between two people, the lower the likelihood that ego knows what an alter knows, limiting ego's ability to seek information effectively and alters' ability to proactively offer relevant novel information to ego. Knowing who has the most information about job opportunities or where to seek funding facilitates the search process even if the information to be transferred is itself not known beforehand. In Uzzi's study of the fashion industry, knowing who possesses information on how to get the best price for wool precedes discovery of that price and where it is offered. Building catalogs of expertise requires prior shared experience, which is a characteristic of strong-tie relationships (Wegner 1987; Liang, Moreland, and Argote 1995; Cramton 2001). More frequent interaction also gives alters a broader catalog of ego's knowledge and interests, making it easier for them to volunteer relevant nonredundant information. For example, alters are more likely to volunteer information about potentially relevant job opportunities if they know that ego is looking for a job and in which industry ego is interested in working.

Search transfer.—While transfer of simple news might be efficient in weak ties, that is not the case for complex information on multiple interdependent topics. Weak ties are inherently limited in the set of novel information they can transfer to the subset of "simple" novel information (Hansen 1999). As Reagans and McEvily (2003) demonstrate, strong embedded ties create a favorable social environment for information transfer: "Cohesion around a relationship can ease knowledge transfer by decreasing the competitive and motivational impediments that arise, specifically the fact that knowledge transfer is typically beneficial for the recipient but can be costly for the source" (Reagans and McEvily 2003, p. 242). Awareness of a previously unknown software module can pass easily via an infrequent social contact. But transferring that module together with interdependent instructions and contextual information requires a level of expert assistance that implies a helping relationship (Hansen 1999).

Information exchanges in embedded relationships are likely to be more

detailed and also more holistic in the sense that they convey not only discrete bits of information but also meta information about how each discrete idea connects with others, as well as discussion of the conceptual implications of each idea. However, structurally diverse bridging ties are usually formed for a particular purpose and in order to deliver information on a single or a limited number of dimensions. Such information is likely to be more discrete, summarizing a number of dimensions in a single signal, such as the price of goods in an economic relationship. Uzzi (1997) describes how representatives of firms engaged in embedded relationships go beyond exchanging price information to also discussing more detailed implications concerning profit margins, fashion sense, and strategy. People can absorb ideas more easily on topics matching their expertise (Cohen and Levinthal 1990), and cohesive embedded ties, in effect those with high bandwidth, have been shown to produce higher rates of complex knowledge transfer in contract R&D (Reagans and McEvily 2003) and product innovation firms (Hansen 1999). Bandwidth therefore affects the ability to share complex forms of novelty.

Knowledge creation.—Creating new knowledge also injects more novelty into the network and often requires rich interaction through thick communication channels. Songwriters and artists benefit from community embeddedness as their ideas feed on one another. In creative works such as country music production, Lingo and O'Mahoney (2010) found two forms of brokerage: one as a strategic actor extracting advantage from network position (the traditional view) and the other as a relational expert connecting others to promote innovation (the creative view). They describe "nexus work" as the iterative process of integrating, synthesizing, and transforming the collective inputs of others. Likewise, in Broadway musicals a team combines initially separate ideas through a creative process of brainstorming, problem solving, and collaboration (Uzzi and Spiro 2005). Such idea-generating collaborations are rarely socially remote. They commonly arise in apprenticeship relationships, for example, between professors and graduate students or between colleagues interacting on the basis of common interests (Lave and Wegner 1991). Obstfeld (2005) finds that brokers who bring together disconnected alters, in effect increasing the frequency of their interactions, promote innovation more than those who keep their contacts separated. Successful innovation teams coordinate their knowledge and actions, intentionally pushing new knowledge to all team members. For instance, initiating design changes to the set of a stage play requires collaborators to update team members quickly and often. These updates to one's social network bring people together and coordinate group action, representing a "union" strategy. In the context of an automotive engineering firm, this strategy was more conducive to trust, cooperation, transfers of complex knowledge, and ultimately idea gen-

eration than "disunion" strategies that kept contacts apart (Obstfeld 2005). In Obstfeld's setting, new social knowledge generated from prolonged contact between engineers helped create innovation, demonstrating how dense cohesive social networks can outperform sparse networks with structural holes.[6]

Homophily.—Homophily among those in cohesive embedded networks makes them more likely to share mutual interests across a wider variety of topics because of similarities across a greater number of distinct social dimensions (Blau 1986; McPherson, Smith-Lovin, and Cook 2001). Though overlapping interests across a greater number of dimensions have been theorized to create redundancy, they can in fact inspire more multifaceted communication, creating opportunities for high-bandwidth channels to deliver more of the different dimensions of information known to each contact. We are more likely to be inspired to cover more topical ground in conversation with those with whom we share a greater number of common interests. Individuals connected by cohesive ties are more likely to engage each other more deeply and to participate in cooperative activities such as joint problem solving, so they are more likely to discover topics of mutual interest in their discussions and to subsequently continue to both generate and exchange information on those additional dimensions (Uzzi 1997; Helper et al. 2000).

In summary, these five social phenomena (social capital, transactive memory, search transfer, knowledge creation, and homophily) imply that as the bandwidth of a channel increases, the topical diversity of information and the total volume of novel information flowing through it should also increase. We therefore expect that *channel bandwidth is positively associated with receiving more diverse information and more total nonredundant information.*

INFORMATION ENVIRONMENTS AND THE CONTINGENCY OF VISION ADVANTAGES

If network diversity and channel bandwidth trade off and if both provide access to novel information, then determining which provides greater information advantages will depend on the information environments in which brokers find themselves. Although a diverse network of weak, low-bandwidth ties ("diverse-low bandwidth") can provide access to more novel information than a cohesive network of strong, high-bandwidth ties ("cohesive-high bandwidth"), the converse is also possible and in many cases more likely. Three characteristics of information environments

[6] We are indebted to one of our reviewers for this helpful insight.

should affect the degree to which bandwidth delivers more novel information to ego. First, the more information overlaps among people in the network, the less structural diversity should confer information advantages. Second, the larger the total size of the topic space, the more important bandwidth becomes in accessing these multiple topics. Third, the more information changes over time, the more cohesive-high-bandwidth networks should deliver novel information.

In the following section we translate our theory into probabilistic expectations of access to novel information in different information environments. These expectations describe how social motivations to exchange more information and the likelihood of greater redundancy in densely connected groups affect the likelihood of receiving novel information from both diverse-low-bandwidth and cohesive-high-bandwidth networks. Each alter has information on certain topics (represented by numbers), which together constitute the set of topics or ideas that exist in the network. The numbers of arrows between actors represent the bandwidths of communication channels (which parallels tie strength).

Consider two actors, Alex (*A*) and Beth (*B*), depicted in figure 2, panel 1. Alex has weak, low-bandwidth ties to unconnected alters Isaac (*i*) and Jake (*j*), whereas Beth has strong, high-bandwidth ties to alters Kim (*k*) and Lauren (*l*), who connect to each other via strong ties. Alex's ties to Isaac and Jake are more likely to be low bandwidth because he is less likely to have sufficient social capital with them to inspire them to share more, he is less likely to know what they know (as are they to know what he needs), they are likely to have less in common and thus are less likely to share information, and they are less likely to create new knowledge together. However, because all three are socially distant, they are more likely to have different information from each other. This scenario captures classic arguments about network structure and information access as well as the diversity-bandwidth trade-off.

Alex's weak-tie contacts, being separated by a structural hole, have no redundant information, whereas Beth's strong-tie contacts, being strongly connected, have redundant information. To demonstrate the importance of the diversity-bandwidth trade-off in even extreme settings that are least favorable to our theory, we invoke the most conservative version of Granovetter's original forbidden triad argument. Although, according to Granovetter, the strong ties connecting *B*-*k* and *B*-*l* imply that the *k*-*l* tie "is always present (whether strong or weak)" (1973, p. 1363), we represent the *k*-*l* tie as a strong connection and assume complete information homogeneity between Kim (*k*) and Lauren (*l*). This same basic scenario holds across all panels 1–6, yet Kim and Lauren frequently provide more novel information to Beth than Isaac and Jake provide to Alex because they furnish a greater overall volume of information. Owing to the high-band-

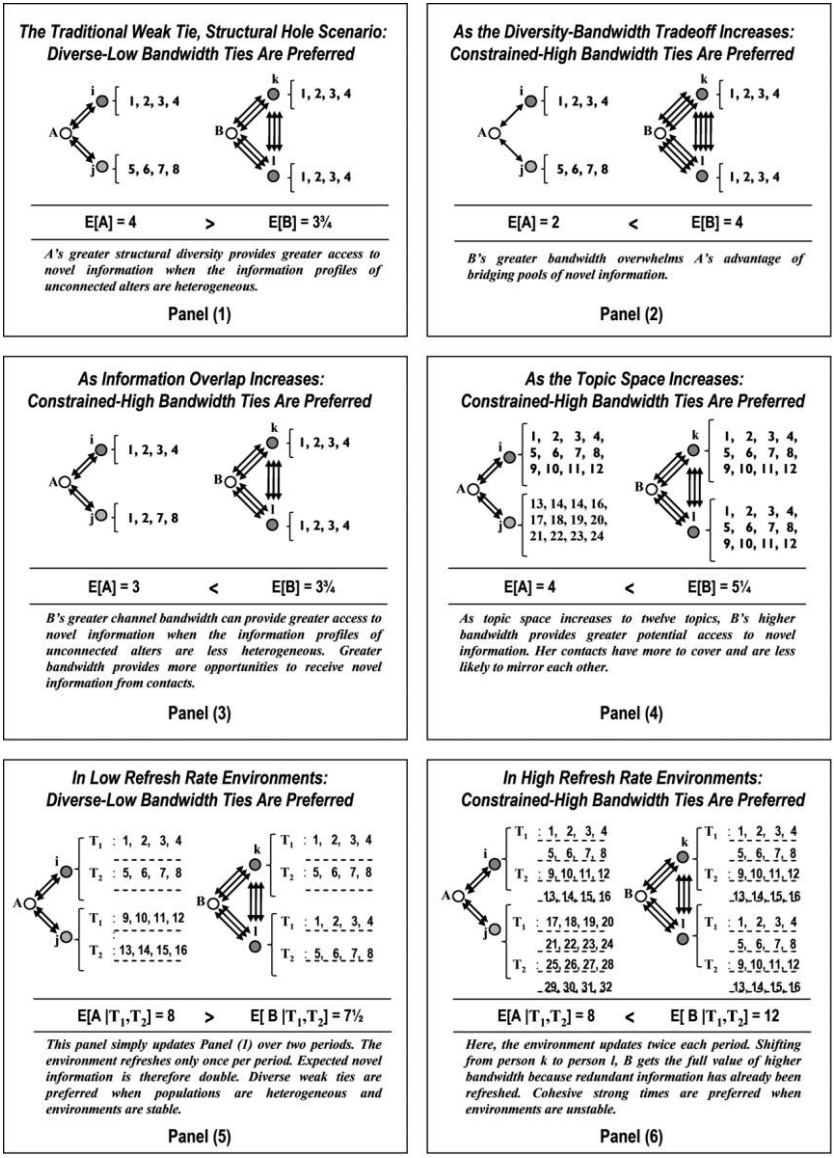


FIG. 2.—The diversity-bandwidth trade-off under varying information environments: (1) a base case, (2) as the strength of the trade-off increases, (3) as the information overlap of alters increases, (4) as the topic space increases, and (5) and (6) as the refresh rate of alters' information increases.

width nature of their relationships, they are more willing and have more opportunities to provide Beth more samples of their respective information spaces. In social terms, whether this extra volume contains extra novelty per unit of information is a trade-off that depends on (i) how much the information of alters overlaps with one another, (ii) the total number of topics in alters' catalog of knowledge, and (iii) the rate at which information in the network refreshes or updates.

The classic weak-tie, structural-hole argument sets the baseline in panel 1, which represents weak- and strong-tie strengths by two arrows and three arrows, respectively. Each alter has information on four topics (i, k, $l = \{1, 2, 3, 4\}$ and $j = \{5, 6, 7, 8\}$), but only Alex's contacts have no overlap in their information. Alex's weak, low-bandwidth ties to Isaac and Jake allow him to secure two samples each from their topic spaces. Beth secures more information samples from Kim and Lauren than Alex does from his alters because of the social processes that characterize their respective information exchanges. Beth has more opportunities to talk with her alters, who are more motivated to share information because of the social pressure, cooperative norms, and cognitive balance that have developed in their embedded relationships. Those factors also make Kim and Lauren less likely to withhold information and more likely to proactively offer information to Beth.

Assuming that alters do not offer the same piece of information twice, Alex samples two nonredundant items from Isaac and two nonredundant items from Jake, receiving four total novel pieces of information overall. Beth, however, will receive three novel pieces of information from her first contact Kim, but there is only a $\frac{1}{4}$ probability that she will receive a novel piece of information in her subsequent exchange with Lauren. If Beth's first draw from Lauren is novel, Lauren has no more nonredundant information to share.[7] Assuming redundant information on her first exchange (which occurs with probability $\frac{3}{4}$), Beth then has a one in three chance of receiving nonredundant information on her second exchange with Lauren. Over these two exchanges, Beth receives novel information with cumulative probability $\frac{1}{2}$ (as given by $\frac{1}{4} + \frac{3}{4} \times \frac{1}{3} = \frac{1}{2}$). If Beth has not received new information by the third exchange (which occurs with probability $\frac{1}{2}$), she retains a $\frac{1}{2}$ chance of receiving nonredundant information in her last exchange. The total chance of Beth receiving novel information over three exchanges is $\frac{3}{4}$ (given by $\frac{1}{4} + \frac{3}{4} \times \frac{1}{3} + \frac{1}{2} \times \frac{1}{2} =$

[7] Since social people talk, it could be the case that Beth tells Lauren what she learned from Kim in order that Lauren shares her nonredundant information in a single draw. But then Beth would already have used her three units of bandwidth. Allowing more targeted requests in a transactive memory sense (Wegner 1987) complicates the analysis but in no way invalidates the basic bandwidth trade-off.

$\frac{3}{4}$). The total number of nonredundant pieces of information Beth expects to receive is thus $3\frac{3}{4}$ given that she started by receiving three nonredundant items from Kim.

If each bit of novel information represents a job opening, then Alex's social network spans eight different opportunities and he can expect to receive news about four of them. In contrast, Beth's social network includes only four opportunities and she can expect, on average, to receive news of fewer opportunities in a given time interval. This is due to the heterogeneity of information among Alex's contacts and demonstrates the value of structural diversity in delivering novel information. Even though Alex has fewer opportunities to exchange information with his contacts, he still expects to receive more novel information because his social network bridges nonoverlapping information pools separated by structural holes.

In panel 2, we examine the same scenario but raise the bandwidth of Beth's ties by one and reduce the bandwidth of Alex's ties by one. The power of bandwidth becomes immediately apparent. While we maintain the same conservative assumptions about the distribution of information across alters (Kim and Lauren have completely redundant information, whereas Isaac and Jake have completely nonredundant information), the increased bandwidth of Beth's ties is enough to provide her with more expected novel information. In fact, the example is trivial. While Alex expects to receive two pieces of nonredundant information (one each from Isaac and Jake), Beth expects to receive four pieces of novel information simply because the bandwidth of her communication channels with Kim and Lauren is higher. In fact, the relative benefit of bandwidth is based on a model that is socially conservative. In their study of R&D transfer, Reagans and McEvily (2003) found that cohesion improves the willingness and ability to transfer information by reducing competition and costs of sharing. Here, Isaac and Jake might have preferred to hoard their unique information either to use themselves or because alters in their positions are more likely to compete, whereas Kim has less incentive to keep from Beth what Lauren can also share.

In panel 3, we relax the conservative assumption of complete information heterogeneity between Isaac and Jake by introducing partial overlap in their information sets.[8] Although Kim and Lauren continue to have completely homogeneous information, the scenario again tips in favor of channel bandwidth: the cohesive-high-bandwidth ties yield more novel information. The only difference in this panel is that Jake's information overlaps with Isaac's information by 50%. Alex still receives two novel

[8] The same insight follows exactly if we instead decrease the overlap of Kim and Lauren rather than increase that of Isaac and Jake.

pieces of information from Isaac but then, on contact with Jake, receives novel information only with probability $\frac{1}{2}$. Assuming that Alex receives no novel information during his first interaction with Jake (which occurs with symmetric probability $\frac{1}{2}$), he will receive novel information during his second interaction with probability $\frac{2}{3}$ as two of the three remaining information items available from Jake are novel. If however, he does receive novel information in his first interaction, the chance of receiving novel information on his second interaction falls to $\frac{1}{3}$. The total probability of Alex receiving novel information over both draws from Jake is 1 (based on interaction one: $\frac{1}{2}$ + interaction two: $\frac{1}{2} \times \frac{1}{3} + \frac{1}{2} \times \frac{2}{3}$). So, Alex expects to receive three total items of novel information, one from Jake and two from Isaac. As Beth's likelihood of receiving novel information has not changed relative to panel 1 (three and $\frac{3}{4}$ from Kim and Lauren, respectively), Beth expects to receive novel information with greater likelihood than Alex in panel 3. This example demonstrates the value of channel bandwidth in delivering novel information even when one's alters have completely overlapping information, which arises from the ability to exchange a greater volume of information with each contact. Panels 1–3 imply the following: *All else equal, we expect that the greater the information overlap among alters, the less valuable structural diversity will be in providing access to novel information.*[9]

In panel 4 we illustrate the effect of a complex or high-dimensional information environment by broadening the overall topic space. Now, alters are aware of 12 topics instead of four. The bandwidths of ties are as they were in panel 1. Alex's contacts Isaac and Jake again have non-redundant information sets and Beth's contacts Kim and Lauren have redundant information sets. As in panel 1, Alex expects four items of novel information, but in this case, because Beth's high-bandwidth ties sample from a broader information space with less chance of collision, she expects more novel information overall. In her first three interactions with Kim, Beth receives three novel items of information, but it is apparent after only her second interaction with Lauren that Beth's total expected novel information exceeds that of Alex. The chain can be established by summing the probabilities of receiving novel information from each of the three interactions. Reduce the denominator once for each

[9] In app. A, we formally prove an even stronger claim. If a weak tie can access all topics in S and a strong tie can access only in-group subset $n_i \subseteq S$, then the strong tie can still provide more access to novel information than the weak tie, provided that n_i exceeds a specific threshold.

draw and reduce the numerator once for each success.[10] On average, receiving three pieces of novel information from Kim and $2\frac{1}{4}$ from Lauren, Beth expects to do better than Alex on the basis of a larger topic space. The difficulty of transferring complex information makes bandwidth even more important in this case. If three units of interdependent information need to be transferred together to be useful, then Beth's benefit of bandwidth is understated. Alex may not be able to use the two pieces of novel information he receives from Isaac and Jake if he has insufficient context to understand them. Likewise, social capital theory also predicts that Beth is better off. It is easier to ask for one item than for 10. Alex must be willing to ask for more and his contacts must be willing to share, but Beth is better positioned to both ask and receive. Further, creativity is often higher when there are more ideas to work with (Weitzman 1998), implying that the value of novel information is higher in the presence of a greater volume of novelty. Panel 4 implies that, *all else equal, the broader the topic space, the more valuable channel bandwidth will be in providing access to novel information.*

Thus far, we have presented the diversity-bandwidth trade-off in purely static contexts in which colleagues' information does not change. A more realistic scenario involves dynamic updating. As we become aware of news concerning our workplaces, our friends, and changes in the world around us, we revise our understanding of basic facts as well as complex know-how. The advance of Internet technologies, mobile service applications for personalized news, and the "always on" nature of online social networks can in fact accelerate the pace at which our knowledge of the world refreshes. Information simultaneously obsolesces as it updates. Environmental turbulence inspires adaptation (Galbraith 1974; March 1991), and changing information makes learning from experience more difficult (Weick 1979). As prior knowledge becomes obsolete more quickly, accessing timely information requires gathering news more frequently.

Reinterpreting a classic example (Granovetter 1973), suppose that highly desirable job openings fill quickly but that undesirable jobs remain open longer. Information drawn from weak ties about the jobs currently available can sample disproportionately from undesirable jobs. By the

[10] The complete chain is given as

$$\frac{9}{12} + \left(\frac{9}{12} \times \frac{8}{11}\right) + \left(\frac{9}{12} \times \frac{8}{11} \times \frac{7}{10}\right) + \left(\frac{9}{12} \times \frac{3}{11} \times \frac{8}{10}\right) + \left(\frac{3}{12} \times \frac{9}{11}\right) + \left(\frac{3}{12} \times \frac{9}{11} \times \frac{8}{10}\right) + \left(\frac{3}{12} \times \frac{2}{11} \times \frac{9}{10}\right) = \frac{9}{4}.$$

As shown in app. A, a more straightforward approach is to use the mean of the hypergeometric distribution, which gives equivalently $3(12 - 3)/12 = 9/4$.

time a weak tie delivers information about a desirable job, information about that job is already well known to competing alters whose strong ties update them more quickly. If information about jobs refreshes often or obsolesces quickly, frequent communication is essential to getting news before others. This speaks directly to the issue of the information refresh rate relative to channel bandwidth. High-bandwidth ties are more likely to deliver time-critical information and are thus more likely to deliver nonredundant information in turbulent information environments. Panels 5 and 6 therefore introduce time.

To reestablish the weak-tie/structural-hole baseline, panel 5 shows that diverse low-bandwidth ties can provide more novel information. In both panels 1 and 5, Beth's contacts' knowledge overlaps whereas Alex's does not; Beth has bandwidth 3 and Alex has bandwidth 2; and information sets span a topic space of 4. But, in panel 5, information refreshes. Dashed lines separate changes in information. Since panel 5 spans two periods (T_1 and T_2), expected access to novel information exactly doubles that of panel 1. Panel 6, however, shows a more turbulent environment. Updates occur twice per period as shown, for example, by the fact that Isaac's information set changes from {1, 2, 3, 4} to {5, 6, 7, 8} within period T_1. Although Beth might learn of three news items (among 1, 2, 3, or 4) from Kim, by the time she checks with Lauren, the context has already changed such that she learns three new items (from among 5, 6, 7, or 8). This gives her six novel pieces of information per period, a full dozen across both periods.[11] High-bandwidth ties can therefore provide more access to new information in more turbulent information environments, despite being more structurally constrained.

In a slow-moving information environment such as roof repair (a roof needs repair roughly once every 20 years), a roofer's network of weak ties is sufficient to deliver information about potential jobs (Podolny 2001). But in turbulent environments such as stock market arbitrage, minute advantages can be critical and people must shift from exploiting what they know to exploring what they do not know quickly and often (March

[11] Although this assumes sequential attention across alters in a given period, the main insights do not change, assuming that ego attends simultaneously to all alters. To model simultaneous draws without replacement on a given alter, use a hypergeometric distribution and then estimate expected nonoverlap. Given complete nonoverlap, the numbers for ego *A* are unchanged across all six panels. For *B* in panel 1, total expected novelty from each alter is 15/8 for a total of 15/4 over both alters. In the sequential draw, Lauren had much higher novelty than Kim, by virtue of getting attention first, namely three versus 3/4. In panel 6, simultaneous draws over each alter provide 39/8 for a total of 9.75. This is lower than the sequential calculation, but higher bandwidth still provides 1.75 more expected novel units of information than structural diversity. Thus, whether using simultaneous or sequential draws, primary intuitions do not change in these examples.

1991). In communications terms, this means interacting more frequently and increasing communication channel bandwidth. For transactive memory systems, change renders the catalog of others' knowledge obsolete, and a person searches less effectively without updates. In the creativity literature, the chance at Schumpeterian recombination of ideas rises as individuals are exposed to change and design changes must be shared with teammates more quickly for projects to be successful (Obstfeld 2005). Constantly changing information implies that ego does not need to change channels to receive incremental novelty because what their contacts have to tell them is itself changing, refreshing, or updating. The greater the bandwidth of communication channels, the more of this newly updated information will be passed on to ego in a timely manner. *We therefore expect that, all else equal, the higher the refresh rate, the more valuable channel bandwidth will be in providing access to novel information.*

Since stylized examples depend heavily on assumptions and initial conditions, we extend these illustrations by developing a more general analytical model of our arguments in appendix A. We formally prove there that each of the factors previously discussed can make either a diverse-low-bandwidth network or a cohesive-high-bandwidth network more attractive in terms of access to novel information. The key intuition is conveyed by representing "bias" as the tendency of cohesive ties to share the same redundant elements from a topic vector. When the disadvantage of bias swamps the advantage of bandwidth, the diverse-low-bandwidth tie provides greater chance of encountering novel information. But when the advantage of bandwidth swamps the disadvantage of bias, the constrained-high-bandwidth tie is preferable. While a range of intermediate cases span these extremes, conditions exist (depending on bias, bandwidth, and the number of links already present) in which a person will always prefer one or the other type of tie (for a summary of hypotheses, see table 2).

The diversity-bandwidth trade-off implies that vision advantages are contingent on the different social settings and information environments in which brokers are situated. In turbulent social settings or intellectual domains where conditions change rapidly and news, ideas, and methods are frequently updated, greater channel bandwidth is more useful for delivering novel information. However, if information possessed by alters is relatively static, structural diversity becomes the more important factor. In highly heterogeneous information environments in which local network neighborhoods possess distinct, nonoverlapping information, bandwidth is less beneficial than structural diversity. But when the overlap of information among alters is more pronounced, the opposite is true. In environments with multiple complex ideas, bandwidth delivers greater novelty, but when the topic space is limited, structural diversity trumps

TABLE 2
SUMMARY OF HYPOTHESES

Domain and Hypothesis	Hypothesized Relationship
Diversity-bandwidth trade-off:	
H1a	Network diversity is positively associated with receiving more diverse information and more total nonredundant information
H1b	Network diversity is associated with lower channel bandwidth
H1c	Channel bandwidth is positively associated with receiving more diverse information and more total nonredundant information
H2a	The greater the information overlap among alters, the less valuable structural diversity will be in providing access to novel information
H2b	The broader the topic space, the more valuable channel bandwidth will be in providing access to novel information
H2c	The higher the information refresh rate, the more valuable channel bandwidth will be in providing access to novel information
Performance effects:	
H3	Access to nonredundant and diverse information is positively associated with individual performance

bandwidth. These contingencies are critical to understanding brokerage because the configurations that produce them are among the most prevalent in human social networks. Since structurally diverse strong ties and cohesive embedded weak ties are both relatively rare (Granovetter 1973; Burt 1992; Watts and Strogatz 1998; Watts 1999; Centola and Macy 2007), the contingent scenarios are the most useful for explaining relationships between networks, information flow, and performance outcomes in a variety of social contexts (see fig. 3).

Unfortunately, the vast majority of empirical work on networks and information advantage is "content agnostic" (Hansen 1999, p. 83). While there is abundant evidence linking social structure to performance (e.g., Burt 1992, 2004, 2007; Reagans and Zuckerman 2001; Sparrowe et al. 2001; Cummings and Cross 2003; Cummings 2004; Aral et al. 2007*a*, 2007*b*), empirical data on information flowing through networked relationships is rarely used to validate information-based theories of brokerage and the strength of weak ties. As Burt (2008, p. 253) notes, "Empirical success in predicting performance with network models has far outstripped our understanding of the way information flow in networks is responsible for network effects. A cluster of network concepts emerged in the 1970s on the idea that advantage results from connections with multiple, otherwise disconnected, groups and individuals. The hubs in a social network were argued to have advantaged access to information and control over its distribution. . . . However, the substance of advan-

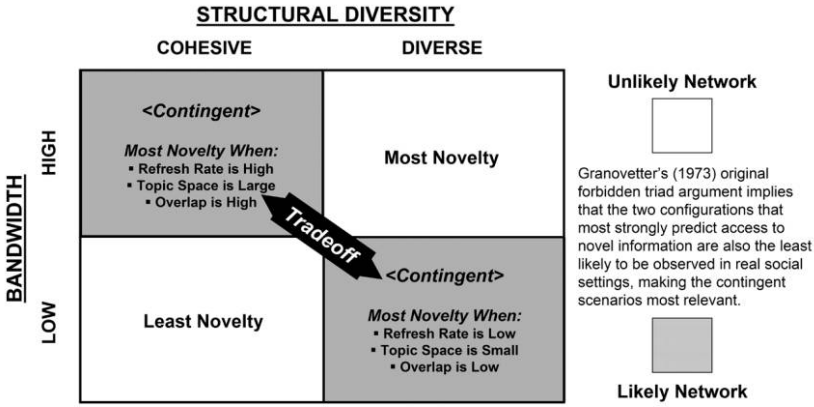


FIG. 3.—Granovetter's (1973) original forbidden triad argument implies that the two configurations that most strongly predict access to novel information (diverse–high-bandwidth ties and cohesive-low-bandwidth ties) are also the least likely to be observed in real social settings, making the contingent scenarios the most relevant. Cohesive-high-bandwidth networks deliver the most novel information when the refresh rate of information is high, when the topic space is large, and when information overlap between alters is low.

tage, information, is almost never observed." According to Burt (2005, p. 60), "The next phase of work is to understand the information-arbitrage mechanisms by which people harvest the value buried in structural holes. . . . More generally, the sociology of information will be central in the work."[12] We therefore test our arguments by combining social network and performance data with direct observation of the information content flowing through e-mail communication.

[12] A significant body of related work in political sociology, research on social movements and on cognition and network structure, has developed around networks and language. Some of this work examines discourse in markets (White 2000), dialogic processes (Steinberg 1999), framing practices (McLean 1998), civic talk (Eliasoph 1996), and commitment styles (Lichterman 1996) in social movements, as well as sociolinguistic approaches to conversational dynamics in social movements (see the work of Harrison White and Ann Mische; e.g., White 1995; Mische and White 1998; Mische 2000). Work on cognition in networks (e.g., Krackhardt 1987, 1990) has examined content from the perspective of what is perceived in and through social networks, and conversation-analytic approaches have been used to examine the structure of interaction (e.g., Goffman 1961; Drew and Heritage 1992; Gibson 2005). We build on this related work by focusing specifically on the diversity and total novelty of information exchanged between actors in networks over time in order to examine the information mechanisms that explain returns to brokerage.

DATA AND METHODS

Research Setting

We collected e-mail messages exchanged by employees of an executive recruiting firm with 14 offices across the United States, analyzing their topical content to determine the relative heterogeneity and novelty of the information passed between the employees. Previous research by Wu et al. (2004) and Kossinets and Watts (2006, 2009) validates the usefulness of e-mail data in characterizing and analyzing social networks in firms and academic institutions. We extend that research by combining analysis of the social structure of e-mail communication with an evaluation of the information content of messages. We argue that combining analysis of message content and communication topology will open new avenues for answering questions at the heart of the sociology of information. Although information flow can be documented in a limited way with ethnographic and survey data (Baker 1984; Reagans and McEvily 2003; Obsfeldt 2005), direct observation of information content and its variation across and movement through networks is critical to accurately testing information-based theories of social capital (Burt 2008).

By analyzing e-mail communication patterns and message content, we are able not only to match network structures to the subject matter of the content flowing through them but also to avoid inaccuracy in respondents' recall of their social networks and communication. Most prior research elicits network data from respondents who have difficulty recalling their networks (e.g., Bernard, Killworth, and Sailor 1981), particularly when contacts are socially distant (Krackhardt and Kilduff 1999). The inaccuracy of respondent recall and the bias associated with recall at social distance create inaccurate estimates of network variables (Kumbasar, Romney, and Batchelder 1994), forcing most empirical studies to artificially limit the boundary of estimated networks to local areas around respondents (e.g., Reagans and McEvily 2003). Such artificial boundaries create estimation challenges due to the sensitivity of network metrics to the completeness of data (Marsden 1990). If important areas of the network are not captured, estimates of network positions can be biased. We therefore took several steps to ensure a high level of participation in the study (described below). As 87% of eligible employees agreed to participate, we collected e-mail network and content data with nearly full coverage of the firm. There are no statistical differences between participants and those who opted out of the study on dimensions of relevance to the analysis.[13]

[13] We performed F-tests to compare performance levels of those who opted out with the performance levels of those who remained, but they did not show statistically

As the company's work was geographically dispersed and instant messaging was rarely used, recruiters relied on e-mail as their primary means of communication.[14] As one recruiter put it, "staff spend an enormous

significant differences: F(Sig): Rev02 2.295 (.136), Comp02 .837 (.365), multitasking .386 (.538). We also calculated the indegrees of missing nodes based on the choices of the nonmissing nodes. We found that the indegrees (insize) of missing nodes were lower than those of nonmissing nodes (average monthly mean indegree nonmissing = 14.7; average monthly mean indegree missing = 10.7); however, t-tests reveal no statistically significant differences between the two (t-statistic = -1.38; $P < .172$). Size is the raw number of contacts and degree is weighted by message counts. We thank an anonymous reviewer for this suggested robustness check.

[14] Most employees we talked to reported that e-mail was their primary means of communication. Although we did not collect phone conversation data or face-to-face information exchanges, e-mail provides the best means of assessing codified communications between employees at this firm. That said, we took several steps to investigate whether use of the phone and use of e-mail were similar in the organization. First, our survey had asked employees to report "the number of people they communicated with on a typical day (*a*) by phone and (*b*) by e-mail." A Pearson correlation returned a .31 correlation, which was significant at the $P < .001$ level, indicating that the sizes of e-mail networks and phone networks were likely to be similar. However, this did not give us insight into network structure, so we went further. Second, we found three reasonable proxies for phone communication between two people. First, our interviews indicated that recruiters most often spoke with their project team members (more than other recruiters in the firm) both by e-mail and by phone. We therefore decided that if two people worked on the same project together, it would be reasonable to expect that they would talk on the phone. In fact, the more projects they worked on together, the more likely they would exchange a greater volume of phone traffic. We therefore constructed a network of "project cowork," which measured as the strength of a tie the number of projects two individuals in the firm had worked on together. Our interviews also indicated that work was frequently regionally clustered (in other words, candidates typically looked for jobs in the same region they were currently working in). We therefore conjectured that if two recruiters worked in the same region, they would be more likely to seek information from one another over the phone about candidates who might be interested in a specific job in that region. Similarly, if they worked in the same office, they may have reasons specific to the social workings of the office to exchange a higher volume of phone communication. We therefore also created two new matrices in which dyads shared a tie if they "worked in the same region" or "worked in the same office." We took these three new matrices, "project cowork," "same region," and "same office," and used Quadratic Assignment Procedure (QAP) to assess QAP correlations and to analyze correlations via Multiple Regression QAP (MRQAP) with a pooled matrix of the total e-mail exchanged between these same individuals (a single pooled matrix of e-mail traffic over all 10 months of data). If these proxies for greater phone traffic (project cowork, same region, and same office) were highly correlated with the e-mail adjacency matrix, then the e-mail network should approximate the phone network. The e-mail network was significantly correlated with the project cowork network (.426, $P < .001$) and with the same region network (.359, $P < .001$), which makes it likely that the e-mail network mirrors the phone network relatively well given that our interviews indicated that recruiters talked more frequently via phone and e-mail to others on the same project or in the same region. Correlation with the same office network was slightly lower (.148, $P < .001$), perhaps because it is less necessary to talk via phone with those in the same office, but also, and perhaps most tellingly, because the cowork network and the same office

amount of time coordinating. We are *big* users of e-mail." The e-mail network of the firm displays a hub and spoke structure, with a dense core of 34 recruiters at the firm's headquarters and spokes in 13 other offices located across the United States (see fig. 4). This structure offers a unique perspective on the value of network and information diversity as measured in e-mail data for two reasons. First, since geographic dispersion makes face-to-face meetings difficult, it establishes e-mail as an even more important source of information (Hinds and Keisler 2002). Second, redundant information and expertise tend to pool in each dispersed geographic location, enabling recruiters with diverse networks to reach across structural holes into distinct pools of information, making this setting particularly well suited to analyzing the information benefits of brokerage.

The core of executive recruiters' work involves matching job candidates to clients' requirements—a process that is information intensive and requires activities geared toward assembling, analyzing, and making decisions based on information gathered from team members, other firm employees, and contacts outside the firm. Recruiters report being more effective when they receive rich information from their colleagues about candidate qualifications, client idiosyncrasies, team coordination, and

network had the lowest correlation (.079, $P < .005$), reflecting the fact that project teams were typically geographically dispersed across different offices—again lending credibility to the argument that project cowork should be a better proxy for phone communication than simply being in the same office. These results mirror the MRQAP results, which indicate that the project cowork network is the strongest predictor of the e-mail network (.339, $P < .01$) and the same region network is also a strong predictor (.225, $P < .01$), whereas the same office network was correlated but was not as strong a predictor (.084, $P < .05$). As our interviews revealed that recruiters talked on the phone most often with those who were on the same projects and in the same regions, the results of the QAP correlations and MRQAP analysis indicate that the e-mail network should mirror the phone network relatively well. A separate question is whether the same type of information is exchanged over the phone and over e-mail. However, the interview evidence that e-mail was the communication medium of choice in this setting gives us confidence that our results of e-mail analyses are the most important in this study with regard to access to information and the role of information in performance. Perhaps more important, phone communication data, if we had them, would likely only support our claims rather than detract from them. If the phone is a richer communication medium through which high-bandwidth, high-novelty information is likely to flow, then the social microprocesses arguments that predict high-bandwidth communication in socially proximate relationships would simply be magnified in the telephone context. For example, we are less likely to have the social capital standing to "cold call" a weak tie to ask for a significant amount of their time to give us detailed novel information, nor would such a tie likely call us out of the blue to volunteer such information. Several of the other social microprocesses operate in the same way in that they predict that social proximity enables high-bandwidth exchanges that are likely to occur over the phone as well as over e-mail. However, future work should assess the differences between phone and e-mail networks.

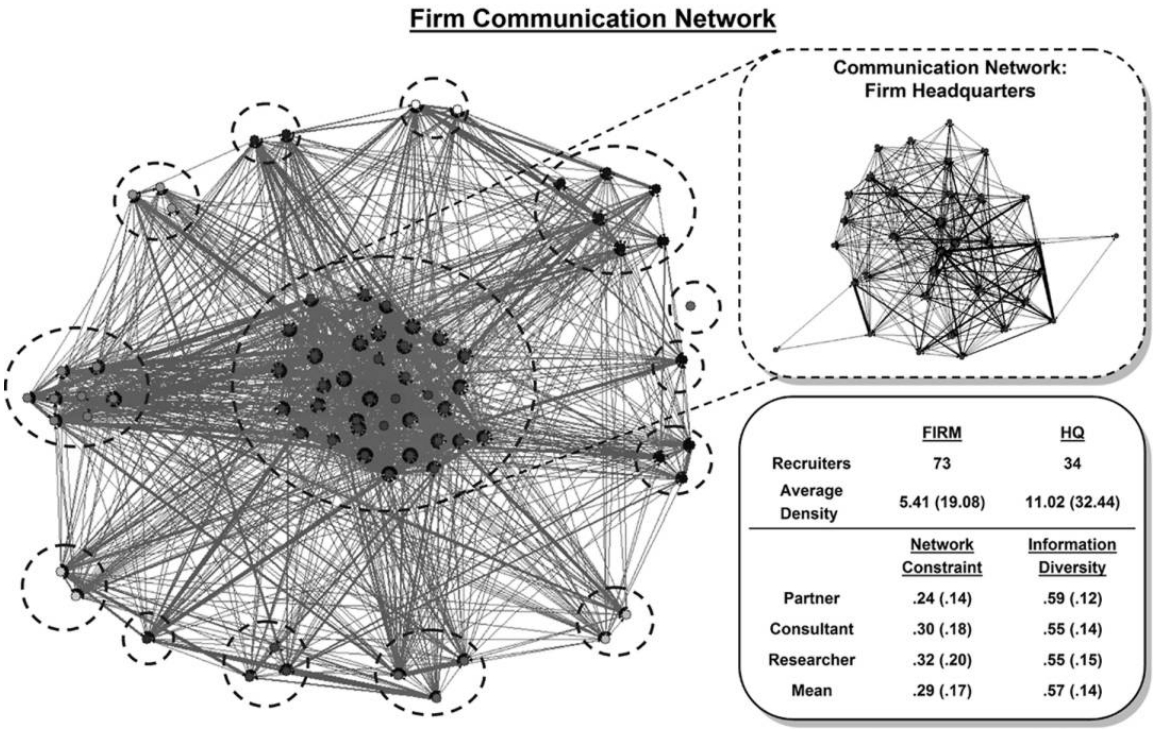


FIG. 4.—The e-mail network of the firm displays a hub and spoke structure, with a dense core in the firm headquarters and spokes in various offices located across the United States.

methods for circumventing secretarial screens or handling difficult placements.[15]

Executive recruiters are quintessential brokers. Access to diverse and novel information is a critical component of their business. Qualitative studies have shown that recruiters fill "brokerage positions" between clients and candidates and rely heavily on information flows to complete their work effectively (Finlay and Coverdill 2000). Information about a diverse pool of candidates, diverse markets, and diverse client firms reduces the time a recruiter wastes interviewing unsuitable candidates and improves the quality of placements (Aral et al. 2007*a*). Sharing procedural information can also improve efficiency and effectiveness (Szulanski 1996). For example, information exchanged through social communication helps recruiters navigate entry into client firms and candidate pools. One recruiter told us that "call penetration can be really hard into private companies so researchers and consultants swap information to get through." Having different information on how to "penetrate" different private companies can make recruiters more effective at gathering the information and contacts they need to match candidates to clients. Information sharing also enables coordination, reducing total work among teams of recruiters searching for similar candidates or clients. As one recruiter told us, "Communication within and across teams is a big success factor. It eliminates double work."

In these ways, recruiters' access to diverse information is critical for filling different types of positions and performing complex matching of candidate strengths and weaknesses to client needs. Recruiters emphasize the need for diverse contacts, reporting that "diversity means more and better contacts" because "skill sets are complementary and not perfectly overlapping." Our interviews also included executive recruiter trainers. One trainer, who describes her job as "helping recruiters learn to be better recruiters," told us, "[To be a successful recruiter one should] develop relationships with people you don't know. . . . Some folks join groups for their prestige but you should join clubs for their diversity." For those reasons we expect diverse and novel information to be particularly important for explaining variance in recruiter performance.

Data

Our data come from four sources: (i) detailed accounting records of individual project assignments and performance; (ii) e-mail data captured directly from the corporate server; (iii) survey data on demographic char-

[15] We conducted in-depth interviews over the course of a year beginning in October 2001.

acteristics, human capital, and information-seeking behaviors; and (iv) data from the website Wikipedia.org used to validate our analytical models of information diversity. The firm gave us complete access to its internal accounting and project databases for records spanning 2000–2005. Those databases describe revenues generated by individual recruiters, contract start and stop dates, projects handled by each recruiter, project team composition, and job levels of recruiters and placed candidates. From those data we were able to mine excellent performance measures that could be normalized for quality. E-mail data include all messages sent through the firm for a period of 10 months, captured from the corporate mail server during two equal periods from October 1, 2002, to March 1, 2003, and from October 1, 2003, to March 1, 2004. Participants received $100 in exchange for permitting use of their data, resulting in 87% coverage of eligible recruiters and more than 125,000 e-mail messages captured.[16] Details of e-mail data collection are described by Aral et al. (2007*a*). The third data set contains survey responses on demographic and human capital variables such as age, education, industry experience, and information-seeking behaviors. Survey questions were generated from a review of relevant literature and interviews with recruiters. Experts in survey methods at the Inter-University Consortium for Political and Social Science Research vetted the survey instrument, which was then pretested for comprehension and ease of use. Individual participants received $25 for completed surveys, and participation exceeded 85%. The fourth data set is made up of 291 entries collected from Wikipedia.org, which we describe in detail in the section pertaining to the validity of our information diversity metrics (see app. C). Descriptive statistics and correlations of all variables are provided in tables 3 and 4 (we detail construction of each variable in the next section). An observation is one person-month.

Variable Construction

Dependent Variables

Recruiters in this firm measure success by the number of job openings filled and the amount of revenue generated per unit of time. We therefore

[16] We wrote and developed e-mail capture software specific to this project and took multiple steps to maximize data integrity. New code was tested at Microsoft Research Labs for server load, accuracy and completeness of message capture, and security exposure. To account for differences in user deletion patterns, we set administrative controls to prevent data expunging for 24 hours. The project went through nine months of human subjects review, and content was masked using cryptographic techniques to preserve privacy (see Van Alstyne and Zhang [2003], U.S. Patent 7,503,070, and Reynolds, Van Alstyne, and Aral [2009] for more detail). Spam messages were excluded by eliminating external contacts who did not receive at least one message from someone inside the firm.

TABLE 3
DESCRIPTIVE STATISTICS

Variable	*N*	Mean	SD	Min	Max
Age	522	42.36	10.94	24	67
Gender (1 = male)	657	.56	.50	0	1
Industry experience	522	12.52	9.52	1	39
Years of education	522	17.66	1.33	15	21
Total incoming e-mails	563	80.31	59.67	0	342
Information diversity	563	.57	.14	0	.87
Total nonredundant information	563	47.94	35.97	0	223.30
Network size	563	16.81	8.79	1	58
Structural holes	563	.71	.17	0	.91
Structural equivalence	563	77.25	16.32	27.35	175.86
Expertise heterogeneity	560	.86	.07	.51	.97
Channel bandwidth	555	5.87	4.13	0	51
Alters' information refresh rate	564	34.24	25.97	0	178.84
Alters' topic space	564	46.59	35.06	0	214.67
Information overlap of alters	564	310.11	362.35	0	3,292.83
Revenue	630	20,962.03	18,843.16	0	80,808.41
Completed projects	630	.39	.36	0	1.69
Average project duration (days)	630	225.23	165.77	0	921.04

assess a recruiter's performance by measuring the number of *projects completed* per month and *revenues generated* per month as recorded in the firm's accounting records. In addition to revenues and project completions, the speed with which vacancies are filled is also an important intermediate measure of workers' productivity. Contract completion implies that recruiters have met a client's minimum thresholds of candidate fit and quality. Project completion can be interpreted as a quality-controlled measure of productivity: a faster rate implies that a recruiter is creating high-quality matches in a shorter period of time. As one recruiter told us, "the longer a client delays, the lower the probability of job acceptance." We therefore also measure *average project duration*.

Network Variables

Network size.—The size of i's network (S_i) is simply the number of contacts with whom i exchanges at least one message. Size is the most familiar network characteristic related to information benefits and is a good proxy for a variety of characteristics, including degree centrality, betweenness centrality, and network reach, which describes the breadth and range of actors' networks (see Burt 1992, p. 12). Network size is significantly correlated with degree centrality ($\rho = .70$; $P < .001$), betweenness centrality ($\rho = .77$; $P < .001$), and reach ($\rho = .56$; $P < .001$)

TABLE 4
PAIRWISE CORRELATIONS BETWEEN VARIABLES

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Age	. . .																	
2. Gender (1 = male)	.11*																	
3. Industry experience	.73*	.20*																
4. Years of education	.38*	.06	.15*															
5. Total incoming e-mail	−.33*	−.10*	−.28*	−.15*														
6. Information diversity	.09	.05	.16*	.05	.29*													
7. Nonredundant information	−.32*	−.09*	−.27*	−.12*	.98*	.36*												
8. Network size	−.07	.02	−.01	.09	.63*	.45*	.64*											
9. Network diversity	.12*	.02	.25*	.01	.34*	.71*	.35*	.62*										
10. Structural equivalence	−.19*	−.06	−.24*	−.06	.23*	−.08	.23*	−.05	−.16*									
11. Expertise heterogeneity	.11*	.20*	.27*	.12*	.03	.23*	.04	.38*	.46*	−.21*								
12. Channel bandwidth	−.24*	−.10*	−.24*	−.20*	.19*	.52*	.50*	−.02	−.02	.29*	−.25*							
13. Refresh rate	−.33*	−.11*	−.26*	−.13*	.95*	.29*	.94*	.61*	.34*	.22*	.09*	.47*						
14. Topic space	−.34*	−.11*	−.30*	−.15*	.97*	.30*	.97*	.62*	.33*	.23*	.03	.50*	.97*					
15. Information overlap	−.25*	−.07	−.19*	−.07	.85*	.20*	.85*	.71*	.30*	.09*	.15*	.27*	.85*	.85*				
16. Revenue	.44*	−.02	.33*	.15*	−.09*	.23*	−.12*	−.12*	.27*	−.16*	.12*	−.05	−.11*	−.14*	−.13*			
17. Completed projects	.41*	−.01	.29*	.11*	−.09*	.23*	−.11*	−.09*	.25*	−.14*	.10*	−.07	−.11*	−.13*	−.13*	.92*		
18. Average project duration	.50*	.12*	.49*	.21*	−.30*	.14*	−.31*	−.07	.18*	−.21*	.07	−.14*	−.32*	−.35*	−.28*	.54*	.47*	. . .

* $P < .05$.

among employees in this organization, demonstrating its value as a proxy for network breadth.

Network diversity.—Network diversity describes the degree to which contacts are structurally nonredundant, and there are both first-order and second-order dimensions of redundancy. We measure redundancy in the first order by the lack of constraint in actors' networks and in the second order by the average structural equivalence of actors' contacts. We define constraint C_i (Burt 1992, p. 55)[17] as the lack of structural holes in an actor's network using bidirectional e-mail traffic to construct ego networks, such that

$$C_i = \sum_j \left(p_{ij} + \sum_q p_{iq} p_{qj}\right)^2, \quad q \neq i, j,$$

and the structural diversity D_i of an actor's network as $1 - C_i$. We use the standard definition of structural equivalence of two actors, measured as the Euclidean distance of their contact vectors (Friedkin 1984).[18] By measuring both network diversity and the structural equivalence of alters, we account for the possibility that small-world networks, or cohesive cliques linked by infrequent weak ties, could bring novel information into a clique (Watts and Strogatz 1998).

Channel bandwidth.—Bandwidth measures the volume of communication over a given channel. As our unit of analysis is the monthly ego network and performance variables are computed monthly, we measure bandwidth by recording average monthly message traffic over communication channels or ties, operationalized as the amount of incoming e-mail over the total number of contacts at time t, providing a measure of the average channel bandwidth of actors' ties:

$$B_{it} = \left(\frac{E_{it}^I}{S_{it}}\right).$$

Information Diversity and Novelty: A Vector Space Model of Communication Content

We model and measure the diversity and total novelty of information in individuals' e-mail using a vector space model of the topics present in e-

[17] The term $p_{ij} + \sum p_{iq} p_{qj}$ measures the proportion of i's bidirectional communication with network contacts that directly or indirectly involve j, and C_i sums this across all of i's contacts.

[18] Euclidean distance measures the square root of the sum of squared distances between two contact vectors, or the degree to which contacts are connected to the same people. We measure the average structural equivalence of actors' direct contacts.

mail content (e.g., Salton, Wong, and Yang 1975).[19] Vector space models represent textual content as vectors of topics in multidimensional space based on the relative prevalence of topic keywords. They are widely used in information retrieval and search query optimization algorithms to identify similar documents or to find topics identified by search terms. In our model, each e-mail is represented as a multidimensional topic vector in which elements are the frequencies of keywords in the e-mail. The prevalence of certain keywords indicates that a topic that corresponds to those keywords is being discussed. For example, an e-mail about pets might include frequent mentions of the words "dog," "cat," and "veterinarian," whereas an e-mail about statistics might mention the words "variance," "specification," and "heteroscedasticity." We evaluated the relative topical similarity of two e-mails by topic vector convergence or divergence—the degree to which their vectors point in the same or orthogonal directions in multidimensional topic space.[20] E-mails about similar topics are more likely to contain similar language, so the vectors used to represent them are closer in multidimensional space, reducing their collective variance, or spread. We therefore measured e-mail content diversity by characterizing all e-mails as topic vectors and measuring the spread of topic vectors in individuals' in-boxes and out-boxes as described below.

Construction of topic vectors and keyword selection.—Our vector space model represents each e-mail D_{il} (where i indexes e-mails and l indexes recruiters) as a vector of keyword frequencies k_{in}. Each e-mail is therefore represented as an n-dimensional vector of keyword frequencies in topic space,

$$\vec{D}_{il} = (k_{i1}, k_{i2}, \ldots, k_{in}),$$

where k_{in} represents the frequency of the nth keyword that appears in the ith e-mail. As terms that appear frequently in an e-mail are more likely to be thematic and to relate to the e-mail's subject matter, we used the "term frequency" of keywords in e-mail as weights to construct topic vectors. An example of the vector construction process is shown in figure 5.

The choice of keywords is an important step in the process. Rather

[19] While e-mail is not the only source of employees' communication, it is one of the most pervasive media that preserve content. It is also a good proxy for other social sources of information in organizations in which e-mail is widely used. In our data, the average number of contacts by phone is positively and significantly correlated with e-mail contacts ($\rho = .31$; $P < .001$). Our interviews indicate that in our firm, e-mail is a primary communication medium.

[20] Each e-mail may pertain to multiple topics on the basis of keyword prevalence, and topic vectors representing e-mails can emphasize one topic more than another on the basis of the relative frequencies of keywords associated with different topics. In this way, our framework captures nuances of e-mails that may pertain to several topics of differing emphasis.

Date: Sun, 01 Feb 2009 10:02:10 -0500
From: xxx@yyy
To: abc@123
CC: zzz@yyy,
abc@zzz
Subject: ~~Re:~~ IWP 1 Extended Thoughts

Actually,

~~To be~~ even more succinct about 3 main take aways:

1. Given ~~our~~ ability ~~to~~ make connections between abstract concepts, ~~our~~ productivity ~~is~~ determined more ~~by our~~ ability ~~to~~ multitask, than ~~by our~~ ability ~~to~~ conduct sequential work faster.

~~So~~, lets explore ~~the~~ mechanisms behind multitasking ~~a~~ bit more:

2. ~~The~~ relationship between output ~~and~~ multitasking ~~is~~ convex ~~at~~ low levels ~~of~~ multitasking ~~and~~ concave ~~at~~ high levels ~~of~~ multitasking (~~Because~~ information inputs ~~are~~ non-rival ~~and~~ complementary, unlike physical inputs, ~~their~~ use enables convexity ~~in the~~ relationship between multitasking ~~and~~ output ~~at~~ low levels ~~of~~ multitasking. Because human information processing ~~is~~ constrained ~~by~~ bounded rationality, ~~and~~ limited cognitive capacity ~~the~~ relationship between multitasking ~~and~~ output ~~is~~ concave ~~at~~ higher levels ~~of~~ multitasking).

~~So~~, how ~~do we~~ acquire ~~the~~ inputs ~~we~~ use?... Socially:

3. Efficient positioning ~~in the~~ social network creates efficient means ~~to~~ gather ~~and~~ use information ~~and is~~ correlated ~~with~~ higher productivity. [~~Because we~~ require ~~a~~ social support system ~~of~~ information acquisition (embodied ~~in our~~ social networks) which ~~we~~ rely ~~on to~~ extend ~~our own~~ individual mental capacity. ~~We~~ gather information inputs socially (~~and~~ through IT ~~which we use as a~~ control variable)]

Dr. XXX

Construction of E-mail Vectors

1. Header information is extracted to create the social network. Names are matched and identities are validated by hand.
2. The subject and body of the e-mail message are analyzed to extract frequencies of use of keywords (Steps 3-6).
3. Stop words (e.g. "a, "an," "the," "and," and other common words) with high frequency across all e-mails are removed as shown by words that have been struck.
4. Keywords are extracted based on the three principles outlined on pages 24-25 of the manuscript.
5. Keywords are root-stemmed, such that for example "multitask," "multitasking," become "multitask*."
6. The frequency of each key word is counted and recorded.
7. A vector representing the e-mail is created which records the e-mail ID, the ID number of each keyword used and the frequency of use of each keyword noted inside brackets as follows: <E-mailID7842B|748821<9>; … ; 849247<2>|>
   A vector representing the example e-mail to the left is shown in truncated form below.
8. The content similarity of e-mail vectors is then compared using several standard distance metrics such as the Cosine distance.

$$\vec{d}_i = (IWP < 1 >; connection^* < 1 >; productivity < 2 >; multitask^* < 9 >; sequential < 1 >; output < 3 >; ...; input^* < 4 >; social^* < 5 >; IT < 1 >; control < 1 >; \text{variable} < 1 >)$$

FIG. 5.—An example e-mail is shown on the left. The step-by-step method used to construct e-mail vectors is described on the right.

than imposing exogenous keywords on the topic space on the basis of our own thinking, we chose keywords likely to characterize useful, representative topics on the basis of the following procedures.[21] First, we initialized our data by removing common "stop words," such as "a," "the," and "and" and other words that appear with high frequency across all e-mails, which are likely to create noise in content measures. We then ran an iterative, k-means clustering algorithm to group e-mails into clusters on the basis

[21] Another common weighting scheme is the "term frequency/inverse document frequency." However, we use a more sophisticated keyword selection refinement method described in detail in the text.

of the co-occurrence of words in e-mails across the entire corpus.[22] The result of iterative k-means clustering is a series of assignments of e-mails to clusters based on their language similarity. These clusters represent "topics" in that they group e-mails with similar topical language.

Second, in order to identify distinct topics in our corpus, keywords should distinguish topics from one another. We therefore chose keywords that maximized the mean frequency variation across k-means clusters, choosing words that tend to appear in the same topic clusters often and in other clusters relatively infrequently. This refinement favors words with widely differing mean frequencies across clusters, retaining words with an ability to distinguish between topics. In our data, we found the coefficient of variation of the mean frequencies of keyword i across topics (C^i) to be a good indicator of this dispersion:[23]

$$C^i = \frac{\sqrt{(1/n)\sum_{c=1}^{n}(m_c^i - \overline{M^i})^2}}{\overline{M^i}}.$$

Third, keywords should *represent* the topics they are intended to identify. To achieve that goal we chose keywords that minimize the mean frequency variance within k-means clusters, favoring words that are consistently used across a large number of the e-mails in a given topic cluster. The intratopic frequency of keyword i (ITF^i) is therefore defined as follows:[24]

$$\mathrm{ITF}^i = \frac{\sqrt{\sum_e \sum_c (f_{ec}^i - m_c^i)^2}}{\overline{M^i}}.$$

Fourth, keywords should not occur too infrequently. Infrequent keywords will not represent or distinguish topics and will create sparse topic

[22] Clustering of k-means generates clusters by locally optimizing the mean squared distance of all documents in a corpus. The algorithm first creates an initial set of clusters based on language similarities, computes the "centroid" of each cluster, and then reassigns documents to clusters whose centroid is the closest to that document in topic space. The algorithm stops iterating when no reassignment is performed or when the objective function falls below a prespecified threshold.

[23] The coefficient of variation is particularly useful because of its scale invariance, enabling comparisons of data sets, like ours, with heterogeneous mean values (Ancona and Caldwell 1992). To ease computation we use the square of the coefficient of variation, which produces a monotonic transformation of the coefficient without affecting our keyword selection. The term C^i refers to the coefficient of variation of keyword i, m_c^i is the mean frequency of keyword i in e-mails in topic cluster c, and $\overline{M^i}$ is the mean frequency of keyword i across all topics.

[24] The letter i indexes keywords and c indexes k-means clusters of e-mails that represent topics; f_{ec}^i is the frequency of keyword i in e-mail e in topic cluster c; m_c^i is the mean frequency of keyword i in e-mails in topic cluster c; and $\overline{M^i}$ is the mean frequency of keyword i across all topics. We squared the variation to ease computation as in n. 23.

vectors that are difficult to compare. We therefore selected high-frequency words (not eliminated by the "stop word" list of common words) that maximize the intertopic coefficient of variation and minimize intratopic mean frequency variation. This process generated topical keywords from usage characteristics of the e-mail communication of employees at our site.[25] We then populated topic vectors representing the subject matter of each e-mail (shown in fig. 5) and measured the diversity and novelty of the streams of e-mail flowing to recruiters over time using the methods described below.

Measures of information diversity and total nonredundant information.—Current literature remains vague in defining the dimensions of novelty or novel information that should matter for vision advantages. We believe that two distinct aspects of novelty are important: the diversity of the information received, which can be thought of as the variance of the topics being discussed, and the total volume of novel information received. We developed two distinct empirical measures of novelty: one that captures variance (which we term "information diversity") and one that captures volume (which we call "total nonredundant information").

We measured the degree to which the e-mails in an individual employee's in-box or out-box are focused or diverse by measuring the spread or variance of their topic vectors. We created five separate diversity measurement specifications based on techniques from the information retrieval, document similarity, and information theory literatures (see app. B for detailed descriptions of each measure). The purpose of all five measures is to characterize the degree to which e-mails are about a set of either focused or diverse topics. We used two common document similarity measures (cosine similarity and Dice's coefficient) and three measures enhanced by an information-theoretic weighting of e-mails based on their "information content."[26] All five diversity measures are highly correlated (~ corr. = .98; see app. B), so our specifications use one of the most common measures, the average cosine distance of employees' incoming e-mail topic vectors d_{ij}^{I} from the mean vector of their topic space M_i^I, to represent incoming information diversity (ID_i^I):

[25] We conducted sensitivity analysis of our keyword selection process by choosing different thresholds at which to select words on the basis of our criteria and found that results were robust to all specifications and generated keyword sets more precise than those used in traditional term frequency/inverse document frequency-weighted vector space models that do not refine keyword selection.

[26] Information content is used to describe how informative a word or phrase is on the basis of its level of abstraction. Formally, the information content of a concept c is quantified as its negative log likelihood, $-\log p(c)$.

$$ID_i^I = \frac{\sum_{j=1}^{N} [1 - \cos(d_{ij}^I, M_i^I)]^2}{N},$$

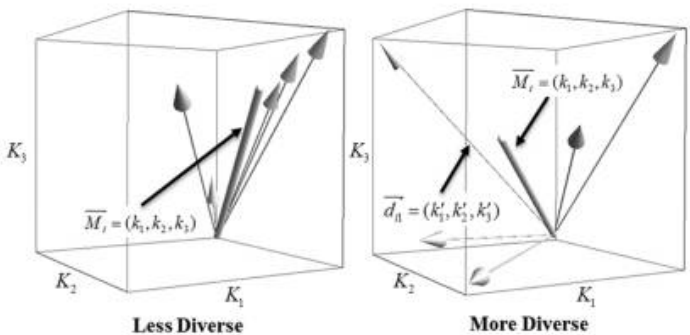
where

$$\cos(d_{ij}, M) = \frac{d_i \cdot M_i}{|d_i||M_i|} = \frac{\sum_j w_{ij} \times w_{Mj}}{\sqrt{\sum w_{ij}^2}\sqrt{\sum w_{Mj}^2}}$$

such that $0 \leq ID_i^I \leq 1$. This measure aggregates the cosine distance of e-mail vectors in an in-box from the mean topic vector of that in-box, approximating the spread or variance of topics in incoming e-mail for a given individual. We measure the total amount of i's incoming e-mail communication as a count of incoming e-mail messages, $E_i^I = \sum_j m_{ji}$, where m_{ji} represents a message sent from j to i, and the total amount of nonredundant information flowing to each actor i as diversity (ID_i^I) times total incoming e-mail: $\mathrm{NRI}_i^I = (E_i^I \times ID_i^I)$. We performed extensive validation tests of our diversity measures by creating simulated e-mail in-boxes using an independent data set from Wikipedia.com. These simulated in-boxes ranged from sets containing highly diverse e-mails about different topics to sets containing highly focused e-mails about a limited number of similar topics. Our measures performed very well in accurately labeling the diverse sets as containing diverse information and vice versa (see app. C). A three-dimensional vector space model of five e-mail vectors and their mean vector is shown in figure 6.

Refresh rate of alters' information (*refresh rate*).—The information refresh rate of an alter j in month t (RR_{jt}) is defined as the cosine distance between every pair of j's daily mean e-mail vectors in that month, including both incoming and outgoing e-mail.[27] In other words, to calculate the degree to which j's information changed from day 1 to day 2 in month t, we calculated the mean vector of j's e-mails on day 1 and the mean vector of j's e-mails on day 2 and then computed the cosine distance between them: $1 - \cos(M_{j\tau_1}, M_{j\tau_2})$. We then repeated this procedure for the mean vectors between day 1 and day 3, day 1 and day 4, and so on until we had dyadic comparisons between each pair of days in month t. We considered measuring the cosine distance only between contiguous days (day 1 and day 2, day 2 and day 3, etc.) but rejected this approach

[27] We measure the refresh rate of alters using both incoming and outgoing e-mail vectors to capture the degree to which information being received was changing and the degree to which alters changed the topics they sent information about over time. Both are likely to affect the effective refresh rate in ego's network. However, an argument could be made for considering the refresh rate of only information received by alters as a proxy for information they are privy to. We therefore created an alternative refresh rate measure that considered only alters' incoming e-mail. Use of that variable did not change the results significantly.



The diversity of the information in an email inbox or outbox is measured by calculating the Cosine Distance of each email vector d_i to the mean vector of that inbox or outbox M_i, and then averaging across all emails:

$$CosDist = 1 - Cos\left(d_{ij}^{I}, M_i^{I}\right)$$

$$ID_i^{I} = \frac{\sum_{j=1}^{N}\left(1 - Cos\left(d_{ij}^{I}, M_i^{I}\right)\right)^2}{N}$$

FIG. 6.—Two different three-dimensional vector space models of separate sets of five e-mail vectors of more (right) and less (left) collective diversity are shown along with their mean vectors on the left. A summary of how information diversity was calculated is shown on the right.

because topics of conversation may simply alternate over days in the week or longer periods. For example, two contacts may e-mail about topic 1 on Monday and topic 2 on Tuesday, go back to topic 1 on Wednesday, and again talk about topic 2 on Thursday. Topics might be repeated every third day, fourth day, or seventh day if there are recurring weekly meetings that inspire e-mail exchanges about those topics. Measuring information dissimilarity only among contiguous days would not capture this potential topic switching and would incorrectly measure these patterns as being very diverse even though a limited number of topics are being repeatedly discussed. We therefore measure the information refresh rate of i's local network P_{it} as a sum of information refresh rates (RR_{jt}) of i's immediate neighbors j in month t, weighted by the strength of ties between i and j. We use the number of messages m_{jit} sent from j to i during month t as a proxy for the strength of incoming ties. Formally, we define the information refresh rate of a node j in month t as

$$RR_{jt} = \sum_{\tau_1 < \tau_2} 1 - \cos(M_{j\tau_1}, M_{j\tau_2}),$$

where $M_{j\tau_1}$ is the mean vector of j's e-mails on day τ_1, and $M_{j\tau_2}$ is the mean vector of j's e-mails on day τ_2. The information refresh rates of i's contacts are then aggregated by summing the refresh rates of i's alters j weighted by the strength of i's incoming tie from each alter: $R_{it} = \sum_j RR_{jt} \times m_{jit}$.

Topic space of alters (*topic space*).—We measure the overall size of the topic space in ego's local network by measuring the total amount of nonredundant information i's alters j exchange with their respective contacts: $\mathrm{NRI}_j = \sum_k (E_{jk} \times ID_{jk})$. If the amount of total nonredundant information i's alters receive and distribute is high, we expect i to be able to sample from a larger topic space. We therefore define the overall topic space of i's network in month t (TS_{it}) as the sum of the nonredundant information of i's contacts in month t weighted by the number of messages sent from j to i during month t (m_{jit}): $TS_{it} = \sum_j \mathrm{NRI}_{jt} \times m_{jit}$.

Information overlap of alters (*information overlap*).—Excessive similarity among alters' topic vectors signals that the information available to ego through different channels may be redundant. The extent to which the information of i's neighbors is redundant depends on the dyadic overlap of all of i's pairs of alters. We therefore calculate the information overlap of each pair of i's alters in month t and average that result over the number of i's contacts in month t:

$$IO_{jkt} = \sum_{k=1}^{N} \cos(M_{jt}, M_{kt})/N.$$

We take the average information overlap between pairs of i's alters so

that the overlap proxy is independent of the number of alters in the network. We then simply sum the average overlap of the information of i's contacts in month t weighted by the number of messages sent from j to i during month t: $IO_{it} = \sum_j IO_{jkt} \times m_{jit}$.[28]

Control Variables

Several additional factors could affect access to diverse novel information and individual performance. We therefore examine six possible alternative explanations for information advantage as control variables: expertise heterogeneity, demography, human capital, total communication volume, unobservable individual characteristics, and temporal shocks to the flow of information in the firm.

Expertise heterogeneity of alters (*expertise heterogeneity*).—A basic premise of brokerage theory is that disconnected network neighborhoods house dissimilar expertise, which brokers tap by reaching across structural holes. If that is true, we would expect individuals with structurally diverse networks to be connected to alters with heterogeneous expertise and that this heterogeneity enables access to novel information. We measure the expertise heterogeneity of an employee's contacts by evaluating the diversity of his or her expertise accumulated through the projects completed in the past. In this setting recruiters develop expertise as they complete projects of different types. As there is little in the way of formal training to become an executive recruiter, we use the distributions of recruiters' prior project experience over project types rather than educational background to measure expertise heterogeneity. The firm categorizes projects into the following categories: chief executive officer, chief operating officer, chief information officer, medical executive, human resources executive, business development executive, nurse, and other. We use these categories as the relevant areas of recruiters' expertise.[29] The expertise heterogeneity variable is constructed using a Herfindahl index of the expertise of an actor's contacts in each month, weighted by the strength of the tie to each alter. As the firm records each employee's effort share on each project, the expertise of a recruiter is share weighted by the amount of effort she recorded against any given project in the accounting data. The measure is constructed as follows:

[28] We exclude each alter's overlap with himself, which would add only a constant to the measure as the cosine similarity of j to j, $\cos(M_{jt}, M_{jt})$, is always 1.

[29] We also ran specifications controlling for other categorization schemes and subcategories of other jobs clustered by their project descriptions, which returned similar results. We therefore retained the firm's original classification.

$$EH_{it} = 1 - \sum_{k=1}^{8} \left(\frac{q_{ik}}{q_i}\right)^2 .$$

In this measure, $q_{ik} = \sum_{j=1}^{n} w_{ij} P_{jk}$ represents the total amount of prior experience in i's network in project class k, weighted by the strength of the tie to each of i's contacts w_{ij} (the number of messages exchanged between i and j) and summed over all of i's contacts j. The term P_{jk} represents j's prior experience in job class k, where P is a count of the number of projects of class k, weighted by effort share, that j has completed. The denominator, $q_i = \sum_{k=1}^{8} q_{ik}$, represents the total project experience in i's network summed over all project classes. Thus the ratio q_{ik}/q_i is the share of prior experience in project class k over the total project experience in i's network. We then construct a Herfindahl index of this ratio measuring the concentration of expertise across job classes among i's contacts. To measure heterogeneity rather than concentration, we subtract that measure from one. As the expertise in i's network becomes more concentrated in a few project classes, the knowledge heterogeneity measure decreases.[30] Reagans and McEvily (2003) construct a similar measure of "expertise overlap," but our measure differs by using accounting records to record project experience (rather than self-reports of expertise) and weights the expertise in an employee's network by tie strength and the effort share of each alter on each project. Our measure of experience heterogeneity also changes over time as recruiters complete more projects of different types.

Demography.—That demography could influence performance, learning capabilities, and the variety of ideas to which individuals have access has been well documented (e.g., Pfeffer 1983; Ancona and Caldwell 1992; Reagans and Zuckerman 2001). Older employees may have related knowledge on a wider variety of topics or may be more aware of experts in the organization. Employment discrimination and interpersonal differences could also affect the relative performance and information-seeking and information-sharing habits of men and women. We therefore control for the age and gender of employees.

Human capital.—Greater industry experience, education, or organi-

[30] To normalize the expertise heterogeneity measure so that its values range from zero to one, we scale the measure by multiplying the final metric by 8/7, creating this final metric:

$$KH_i = \frac{8}{7}\left[1 - \sum_{k=1}^{8} \left(\frac{q_{ik}}{q_i}\right)^2\right].$$

This scaling does not affect the distribution of the measure or the outcome of any of our analyses. It simply allows the measure to range from zero to one, easing interpretation.

zational status could also create variation in access to diverse and novel information and performance. As individuals gain experience, they may collect expertise across several domains, reflected in communications across multiple subjects or topics. It could also be that individuals specialize as they gain experience, focusing their work and communication on a limited number of topics. We therefore control for the level of education, industry experience measured by the number of years employees have worked in executive recruiting, and organizational position. As employees occupy one of three positions in the firm—partner, consultant, or researcher—we include dummy variables for these positions to account for authority and status differences that could explain variation in both access to information and performance.

Total communication volume.—We are interested in both the total amount of novel information and the importance of network structure holding communication volume constant. Other studies have demonstrated the importance of controlling for communication volume to isolate the effects of structural variables (e.g., Cummings and Cross 2003). We therefore control for total e-mail communication.

Individual characteristics and temporal shocks.—Some employees may simply be more social or more ambitious, creating variation in information-seeking habits and performance. To control for unobservable individual characteristics, we test fixed-effects specifications of each of our hypotheses. Temporal shocks could also affect demand for the firm's services, with additional work stimulating information-seeking activities. In our data, business exhibits seasonal variation. Demand for the firm's services picks up sharply in January and declines steadily through the next eight months. These exogenous shocks to demand could drive simultaneous increases in project workload, information seeking, and revenue generation and create a spurious correlation between information flows and output. There could also be nonseasonal transitory shocks to demand in a given year or a given month of a given year. We control for seasonal and transitory variation in our data by using dummy variables for each month and year. Figure 7 visualizes the expertise heterogeneity and information diversity variables by showing how project experience in different job classes and topics discussed in e-mails were distributed across a group of five recruiters.[31]

[31] Multicollinearity is not a significant issue in our study for several reasons. First, we never include any of the variables with a high correlation in the same model, making multicollinearity due to their simultaneous inclusion in an estimating equation unlikely. Second, we conducted variance inflation factor (VIF) analysis, which provides a measure of the degree to which the variance of an estimated regression coefficient is increased as a result of multicollinearity, to quantify the severity of the effects of multicollinearity in our models. We examined the VIF for all coefficients in all of our

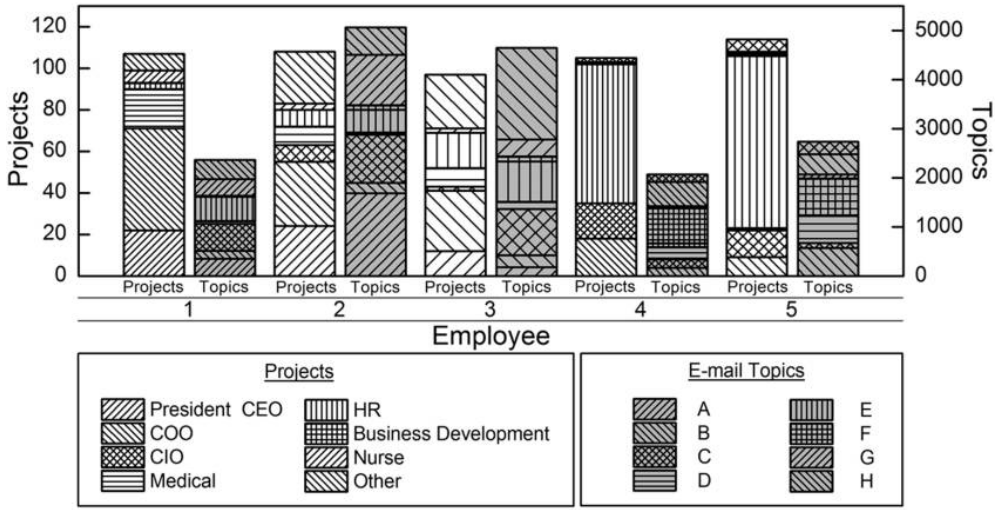


FIG. 7.—Distributions of project expertise and topics in incoming e-mail are shown for five recruiters. Distributions of project expertise represent the proportions of expertise of each of the five recruiters over the eight project categories recognized by the firm. Distributions of topics in incoming e-mail represent the number of incoming e-mails that discuss each of eight topics A–H (an e-mail can contain reference to more than one topic).

Model Specification

We used panel data to estimate relationships between network structure and information access and between information access and performance. We are interested in how variations in network structure explain performance differentials between individuals, as well as how changes in actors' networks explain variation in their access to information and performance. If network structure generates social capital by influencing information access, actors who possess larger, more diverse networks with higher channel bandwidth should receive more novel information and perform better than their counterparts. However, unobserved heterogeneity in employees' personal characteristics, such as ambition, gregariousness, or social in-

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specifications. None of the variables listed above ever generated a VIF greater than 5, which is well below the acceptable threshold of 10 noted by Kutner, Nachtsheim, and Neter (2004). The only two variables that ever recorded VIFs greater than 5 were the network size and network size squared variables when they were simultaneously entered into regressions, which is common for nonlinear terms. We therefore estimated these regressions with the network size squared term removed, which created no qualitative change in the parameter estimates or the significance of any of the variables in the models. We choose to include the size squared term, however, if it was significant in order to document the nonlinear effects of size and to remove it in cases in which it contributed no explanatory power. Third, the real danger of multicollinearity is to bias parameter estimates toward zero by inflating the variance of an estimated regression coefficient. As such, any variance inflation due to collinearity should serve only to make our estimates more conservative (by making confidence intervals wider) and to therefore make it more difficult to estimate statistically significant results. The parameters of interest are significant even if there is variance inflation due to collinearity. Fourth, aside from statistical concerns such as variance inflation due to multicollinearity, we also considered the theoretical implications of these constructs being highly correlated. The measures we have devised are theoretically and conceptually distinct and produce different results in our analyses that are theoretically interesting and make sense from the perspective of our theory. For example, in the case of total nonredundant information and information diversity, we discuss in the article how these variables are conceptually related in that the first is a proxy for the "volume" of novel information and the second is a proxy for the "variance" of information or topics. We discuss in some depth why these distinctions are important and why we believe they are significant in some models but not in others. We have also added to and clarified this discussion to bring it to the fore. Furthermore, the raw correlation is a particularly uninformative summary statistic in this case. When we consider the correlation of these two variables over their joint distributions, we find that they are highly uncorrelated in particular regions and highly correlated in others. In particular, when the volume of novel information is low, the diversity of information is low as well, and they are highly correlated. However, they display a correlation of only .12 for values of information diversity greater than 1 SD less than the normalized mean. The zero-order correlation is driven by their high correlation at low levels, which makes sense. In the limit, when you receive no e-mail, you receive no novel information and the diversity of your incoming information is also zero. Epsilon perturbations from this limit exhibit similar high correlations. However, as we get into more interesting regions of the distributions, the correlation of these variables decreases significantly as expected and described above.

telligence, could simultaneously drive variation in network structure and performance. If unobserved characteristics of individuals are correlated with the error terms in our models, pooled ordinary least squares (OLS) estimation will produce biased parameter estimates. To control for bias created by unobserved heterogeneity, we examine variation within and across individuals over time using both fixed-effects and random-effects models. As observations in network data are not independent, we estimate a model of network autocorrelation of disturbances that provides consistent estimates of coefficients and standard errors that are robust to both network and temporal autocorrelation in panel data. Full details of our model specifications and estimation procedures are provided in appendix D.

RESULTS

The Diversity-Bandwidth Trade-off

If the diversity-bandwidth trade-off regulates the receipt of novel information, we should observe two phenomena in our data. First, as recruiters' networks become more diverse, we should see the bandwidth of their communication channels contract. Second, they should receive more novel information as their networks become more structurally diverse and as channel bandwidth expands. If those conditions hold, then a trade-off between network diversity and channel bandwidth is creating countervailing effects on the receipt of novel information.

We found strong evidence confirming the diversity-bandwidth trade-off. As recruiters communicated with contacts who were less well connected to each other and who occupied less structurally equivalent positions in the network, the bandwidth of their communication channels to those contacts contracted quite rapidly. For instance, we estimated that a 1-SD increase in the structural diversity of a recruiter's network over time was associated on average with a 21% reduction in the bandwidth of his or her communication channels (models 1–3, table 5, $P < .01$). As recruiters communicated more with contacts who were themselves densely connected and structurally equivalent, the bandwidth of their communication channels expanded. There was a strong negative relationship between network diversity and channel bandwidth (table 5, model 1: $\beta = -.314$, $P < .01$) and a strong positive relationship between structural equivalence and channel bandwidth (table 5, model 1: $\beta = .107$, $P < .05$), indicating that as networks became more diverse, the thickness of communication channels narrowed. These results held even when we controlled for network size and expertise heterogeneity in fixed-effects models that also hold unobserved time-invariant heterogeneity constant

across recruiters (table 5, models 1–3). We also found that both greater network diversity and greater channel bandwidth were strongly associated with the receipt of more diverse information and more total nonredundant information (network diversity: table 6, as discussed in the next section, models 2 and 9, $P < .01$; channel bandwidth: table 6, models 4, $P < .05$, and 10, $P < .01$). Having established that the diversity-bandwidth trade-off regulates access to novel information, we then examined the conditions under which this trade-off affects vision advantages.

In the organization we studied, work was organized by geographic regions and knowledge domains. Recruiters with diverse networks communicated with contacts whose prior experience and knowledge were heterogeneous, providing evidence of one way in which diverse networks deliver diverse information—by providing access to pools of heterogeneous expertise. This mechanism is reflected in the strong positive association between expertise heterogeneity and network diversity in models 6–10 in table 5. In order to contact peers with varied expertise, recruiters diversified their communication networks (communicated with structurally distant alters) to reach across structural holes into local network neighborhoods less well connected to their own. This confirms earlier findings on the diversity of expertise in networks rich in structural holes (Reagans and McEvily 2003; Rodan and Gallunic 2004) and supports a basic premise of brokerage theory: that disconnected network neighborhoods house dissimilar expertise and knowledge, which brokers tap by reaching across structural holes. However, as recruiters began to reach into diverse, unconnected network neighborhoods seeking advice, information, or support, the bandwidth of their communication channels decreased (table 5, models 1–5 and 8–10). The negative associations between expertise heterogeneity and channel bandwidth in pairwise correlations ($\rho = -.25$, $P < .05$), random-effects models ($\beta = -.21$, $P < .01$, model 5), and more conservative fixed-effects models ($\beta = -.095$, $P < .10$, model 3) provide corroborating evidence for the diversity-bandwidth trade-off. Individuals whose contacts had diverse knowledge and experience communicated more infrequently and with lower volume per channel, which is consistent with prior characterizations of the nature of weak-tie relationships (Granovetter 1973; Uzzi 1996) and provides new empirical evidence about how information tends to flow through them.

To create more diverse networks, recruiters must cultivate new structurally distant contacts, which increases their network size. Limited time, energy, and attention could necessitate weaker, more infrequent, and therefore lower-bandwidth communication with those contacts, an argument consistent with the notion of network maintenance costs (Burt 1992). Interestingly, however, our findings show that the reductions in channel bandwidth associated with greater network diversity do not seem

TABLE 5
THE NETWORK DIVERSITY–CHANNEL BANDWIDTH TRADE-OFF

	Dependent Variable: Channel Bandwidth					Dependent Variable: Network Diversity				
	Model 1 FE	Model 2 FE	Model 3 FE	Model 4 RE	Model 5 RE	Model 6 FE	Model 7 FE	Model 8 FE	Model 9 RE	Model 10 RE
Age					−.006					−.007
					(.011)					(.006)
Gender					−.113					−.129*
					(.136)					(.070)
Education					−.123**					−.012
					(.059)					(.030)
Industry experience					−.014					.012*
					(.012)					(.006)
Partner					.145					.155
					(.284)					(.145)
Consultant					−.231					.174
					(.217)					(.110)
Network diversity	−.314***	−.288***	−.335**	−.286***	−.190*					
	(.078)	(.095)	(..136)	(.089)	(.111)					
Structural equivalence	.107**	.101*	.105*	.167***	.149**	−.055	−.033	−.021	−.034	−.073**
	(.042)	(.052)	(.055)	(.054)	(.068)	(.038)	(.031)	(.030)	(.0267)	(.030)

Expertise heterogeneity ...		−.074	−.095*	−.209***	−.141**	.254***	.132***	.127***	.132***	.122***
		(.056)	(.049)	(.058)	(.068)	(.019)	(.019)	(.025)	(.029)	(.031)
Network size			.213	.476***	.398**		.747***	.753***	.965***	.911***
			(.231)	(.171)	(.199)		(.102)	(.102)	(.074)	(.078)
Network size squared			−.123	−.345**	−.333**		−.445***	−.446***	−.612***	−.543***
			(.149)	(.142)	(.161)		(.073)	(.073)	(.065)	(.066)
Channel bandwidth								−.076***	−.069***	−.037*
								(.028)	(.021)	(.021)
Constant	.181***	.192***	.164***	.105	2.793***	.342***	.199***	.202***	−.034	.530
	(.046)	(.047)	(.047)	(.124)	(.972)	(.036)	(.040)	(.037)	(.062)	(.503)
Temporal controls	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year
F-value/Wald χ^2	45,938***	125.91***	788.77***	74.63***	76.63***	112,301***	2,479.08***	1820***	425.64***	408.09***
(*df*)	(11)	(12)	(14)	(13)	(19)	(11)	(13)	(13)	(13)	(19)
R^2	.09	.09	.10	.20	.24	.23	.35	.35	.55	.59
N	536	535	535	535	429	538	538	535	535	429

NOTE.—Hausman test results: random effects (RE) consistent and efficient, models 3 and 4: 21.23*, $P < .10$; models 7 and 8: 411.38***, $P < .01$.

* $P < .10$.

** $P < .05$.

*** $P < .01$.

to be driven only by the time and effort costs of network maintenance, but also by the nature of the relationships in sparse networks. The positive parameter estimate on the network size variable in bandwidth regressions (table 5, models 4 and 5) indicates that, as recruiters cultivated more contacts, the bandwidth of their communication channels widened rather than narrowed. If constraints on time and effort devoted to relationship maintenance alone were driving channel bandwidth, we would expect bandwidth to decrease as network size increased. On the contrary, as recruiters communicated with more people, they also exchanged more messages per contact.

As network size continued to increase, time, energy, and attention constraints eventually had their expected effect. The network size squared estimate on channel bandwidth is negative and significant in random-effects specifications, indicating declining marginal increases in channel bandwidth as networks grew. The nonlinear relationship between network size and channel bandwidth suggests that there are simultaneous increases in network size and channel bandwidth in smaller networks but that as network size exceeds the normalized population mean, time and effort costs and the nature of weak-tie relationships necessitate reductions in channel bandwidth (see fig. 8). Evidence of this maintenance cost mechanism was seen only in random-effects models that consider variation between recruiters and not in fixed-effects models that analyze variation within observations of recruiters over time. This suggests that unobserved heterogeneity between recruiters explains this variation. For instance, more gregarious recruiters could have larger networks and could communicate more with each contact on average up to a certain network size.

Models 7–10 in table 5 also show a strong positive, but nonlinear, relationship between network size and network diversity. These results suggest that information benefits to larger networks are constrained in bounded organizational networks and that marginal benefits to structural diversity decrease as a network grows in size. As recruiters contacted more colleagues, each new contact contributed a diminishing amount of structural diversity to the focal actor's network. The implications of this trade-off between size and structural diversity complement Burt's (1992, p. 167) concepts of "effective size" and "efficiency."[32] Figure 8 graphs the relationships among network size, network diversity, and information diversity, clearly showing the positive, nonlinear relationships.

Demographic variables have no effect on channel bandwidth in models 4 and 5, whereas education has a consistently negative relationship, per-

[32] In fact, Burt (1992, p. 169) finds stronger evidence of hole effects with the constraint measures we employ than with effective size, demonstrating that "exclusive access is a critical quality of relations that span structural holes."

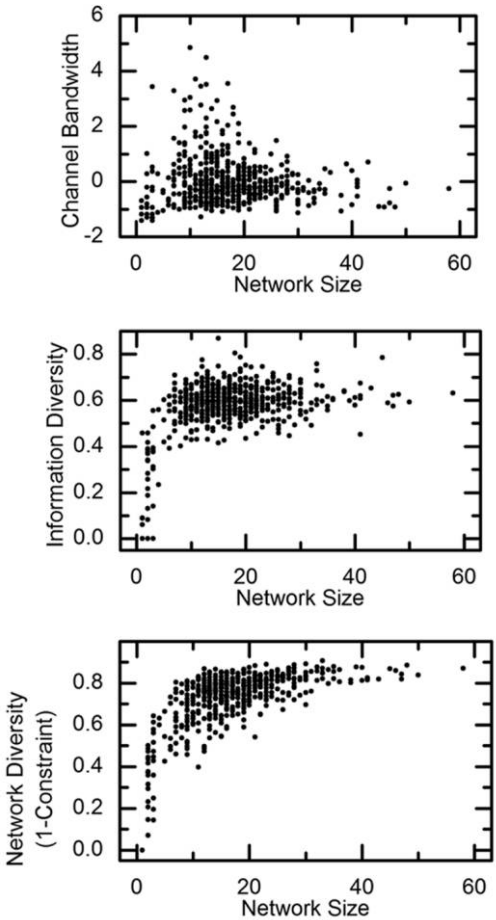

FIG. 8.—Relationships between network size, bandwidth, network diversity, and information diversity.

haps indicating that more educated employees are able to communicate more efficiently with fewer messages per channel. Fixed- and random-effects models are relatively consistent, except that network size and expertise heterogeneity variables are correlated with channel bandwidth only in random-effects models, indicating that persistent variation in network size and expertise heterogeneity between individuals explained variation in channel bandwidth, whereas changes in individuals' network size and network expertise heterogeneity over time did not. However, changes in network diversity do explain changes in bandwidth over time. As recruiters' networks became more structurally diverse, the bandwidth

of their communication channels contracted. Taken together, these results again confirm the trade-off between diversity and bandwidth.

The Diversity-Bandwidth Trade-off and Access to Novel Information

If vision advantages exist and are regulated by the diversity-bandwidth trade-off, we should observe positive effects from network diversity and channel bandwidth on the receipt of diverse novel information. Analyses estimating whether network diversity and channel bandwidth predict incoming information diversity (ID^I_{it}) and total nonredundant information received (NRI^I_{it}) are shown in table 6.[33]

We found strong support for the basic argument that information benefits explain returns to structural diversity and brokerage. Network diversity was positively and significantly associated with greater information diversity in incoming e-mail. The first-order diversity variable, which measures the lack of constraint in recruiters' networks, was highly significant in all specifications, whereas the average structural equivalence of recruiters' contacts did not influence access to diverse information (controlling for network size and first-order structural diversity). A 1-SD increase in network diversity was associated with approximately a 0.15-SD increase in the diversity of incoming information, demonstrating that large diverse networks provide access to diverse information. The expertise heterogeneity of recruiters' contacts was positively correlated with the diversity of the information recruiters received in both pairwise correlations (.23, $P < .05$, table 4) and regression results (table 6, model 1). When we control for total communication volume, a 1-SD increase in the expertise heterogeneity of recruiters' contacts was associated with a 0.28-SD increase in incoming information diversity (model 1, $P < .01$). When the network diversity and structural equivalence terms were added to the estimation (model 2), the positive contribution of expertise heterogeneity to incoming information diversity was reduced by 75%, implying that network diversity and expertise heterogeneity are positively correlated and that network diversity is a stronger predictor of access to diverse information than the expertise heterogeneity of recruiters' contacts.

As recruiters reached across structural holes, they were not only communicating with those who had more diverse sets of expertise but were also receiving more diverse information from their contacts as a result.

[33] We focus in this article on incoming information for two reasons. First, we expect network structure to influence incoming information more than outgoing information. Second, the theory we intend to test is about the information to which individuals have access as a result of their network structure, not the information individuals send. These dimensions are correlated.

This corroborates the theory that network diversity provides diverse information in part by providing access to diverse pools of expertise, but it also confirms that in our setting, network structure is a stronger predictor of access to diverse information than the expertise heterogeneity of ego's contacts.

As recruiters added network contacts, the contribution to information diversity lessened with each additional contact, implying diminishing marginal information benefits to larger networks. A 1-SD increase in the size of recruiters' networks (approximately eight additional contacts) was associated with a 0.5-SD increase in information diversity (models 3–7, $P < .01$); the coefficient on network size squared was negative and significant, indicating diminishing marginal information benefits to network size (models 3–7, $P < .01$).[34]

Finally, channel bandwidth was also associated with access to more diverse information, confirming that the diversity-bandwidth trade-off was regulating access to diverse information. A 1-SD increase in channel bandwidth was associated with a 0.085-SD increase in information diversity (model 4, $P < .05$). When channel bandwidth was added to the specification, the magnitude of the estimated relationship between network diversity and information diversity increased. This implies a negative correlation between network diversity and channel bandwidth, providing additional corroborating evidence of the trade-off between the two.

While models 1–7 in table 6 estimate correlates of information diversity, models 9–13 show that the total volume of novel information flowing to recruiters increased with their network size, network diversity, and channel bandwidth. Expertise heterogeneity had a strong positive relationship with total nonredundant information received (model 8, $P < .01$), until the network diversity and structural equivalence variables were added to the specification (model 9), again demonstrating that recruiters accessed novel information by reaching across structural holes into diverse pools of expertise. Network diversity and channel bandwidth both had strong positive relationships with the total amount of novel information flowing into actors' in-boxes (model 10, $P < .01$), with a 1-SD increase in bandwidth associated with a 0.35-SD increase in total novel information received ($P < .01$). As network size and the thickness of channels increased, the total volume of novel information received also increased. These results demonstrate the importance of considering channel bandwidth, as well as the diversity-bandwidth trade-off, when estimating relationships between network structure and access to diverse novel information. Bandwidth trades off with network diversity and has a strong positive rela-

[34] We also tested a negative exponential specification of this relationship with very similar results.

TABLE 6

EFFECTS OF NETWORK DIVERSITY AND CHANNEL BANDWIDTH ON ACCESS TO DIVERSE, NOVEL INFORMATION: FIXED-EFFECTS SPECIFICATIONS

	Dependent Variable: Information Diversity							Dependent Variable: Nonredundant Information					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Total e-mail incoming	.002**	.000	−.001	−.002*	−.002**	−.005***	−.002						
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)						
Expertise heterogeneity	.281***	.073***	.028	.037*	.035*	.032	.037*	.181***	.099***	−.011	−.010	.0002	−.007
	(.054)	(.023)	(.019)	(.021)	(.019)	(.020)	(.021)	(.026)	(.030)	(.016)	(.019)	(.018)	(.023)
Network diversity		.232***	.145*	.155*	.161**	.165**	.139**		.206***	.066**	.016	.045**	−.036
		(.062)	(.083)	(.083)	(.075)	(.071)	(.095)		(.072)	(.032)	(.016)	(.016)	(.043)
Structural equivalence		.012	.019	.021	.024	.027	.017		−.032	−.007	.012	.007	.008
		(.042)	(.045)	(.036)	(.040)	(.040)	(.035)		(.041)	(.049)	(.007)	(.004)	(.033)
Network size			.439***	.505***	.485***	.488***	.468***			.668***	.231***	.115***	.161**
			(.102)	(.105)	(.069)	(.069)	(.091)			(.102)	(.030)	(.019)	(.050)
Network size squared			−.250***	−.259***	−.257***	−.256***	−.216***						
			(.065)	(.054)	(.051)	(.053)	(.067)						
Channel bandwidth				.085**	.081**	.084**	.080**			.352***	.120***	.060***	.201***
				(.041)	(.033)	(.032)	(.040)			(.067)	(.030)	(.011)	(.051)
Refresh rate					.028						.642***		
					(.070)						(.040)		

Channel bandwidth × refresh rate					−.016						.077***		
					(.037)						(.009)		
Topic space						.210						.832***	
						(.146)						(.044)	
Channel bandwidth × topic space						−.009						.037**	
						(.036)						(.017)	
Information overlap							−.003						.638***
							(.037)						(.079)
Network diversity × information overlap							−.038						−.230**
							(.043)						(.076)
Constant	−.456***	.004	.064	.165	.248**	.408***	.152	−.172***	.371***	−.131***	−.012	−.045***	.215***
	(.068)	(.088)	(.077)	(.111)	(.106)	(.093)	(.107)	(.021)	(.041)	(.037)	(.017)	(.014)	(.033)
Temporal controls	Month/year	Month/year	Month/year	Month/year	Month/year	Month/year	Month/year	Month/year	Month/yearr	Month/year	Month/year	Month/year	Month/year
F-value/Wald χ^2	6.6E4***	6,994***	492.8***	97.32***	80.06***	374.1***	269.9***	4.6E5***	1.0E5***	333.5***	9,845***	2,976***	27,960***
(df)	(11)	(13)	(15)	(16)	(18)	(18)	(18)	(10)	(12)	(14)	(16)	(16)	(16)
R^2	.14	.11	.14	.16	.16	.16	.16	.18	.19	.56	.86	.91	.75
N	556	538	538	535	535	535	535	556	538	535	535	535	535

* $P < .10$.
** $P < .05$.
*** $P < .01$.

tionship with incoming information diversity and total nonredundant information, creating countervailing effects on the information benefits to brokerage.

Although network diversity predicts both the diversity and the total amount of novel information actors receive, the coefficient on network diversity drops by 66% when network size and channel bandwidth are added to the specification. A 1-SD increase in channel bandwidth was associated with a 0.35-SD increase in total nonredundant information received, whereas a 1-SD increase in network diversity was associated with only a 0.07-SD increase. These results imply that while structural diversity and channel bandwidth both have a strong impact on the *diversity* of the information actors receive (per unit of information), variation in the total *amount* of novel information received is determined mostly by the size of actors' contact networks and their channel bandwidth, drawing attention to the importance of the thickness of communication channels and the number of contacts in providing larger total volumes of novel information.

To investigate how the diversity-bandwidth trade-off behaved in different information environments, we examined the effects of the refresh rate, the size of the topic space, and information overlap on relationships between network diversity, channel bandwidth, and access to novel information. Implications of variation in the refresh rate are shown in table 6, models 5 and 11. When the refresh rate of alters' information increased, recruiters received more novel information and channel bandwidth had a stronger effect on the volume of novel information received (model 11). In other words, as alters' information changed more from day to day, higher-bandwidth ties to those alters delivered more total nonredundant information. Interestingly, the refresh rate did not have the same effect on the average diversity of information received—the variance of topics (model 5).

As the topic space of alters' information increased, recruiters received more total nonredundant information from their contacts and greater channel bandwidth provided even more total nonredundant information than when the alters' topic space was smaller (model 12). Communicating through thicker channels with those who know about many topics affords an ability to sample more information on distinct topics. As these models are estimated using fixed-effects specifications, the variation comes from changes in the topic space of a recruiter's alters over time. As the topic space of recruiters' contacts increased, they received more novel information and their high-bandwidth ties were even more valuable in delivering more novel information.

These two results highlight why the distinction between information diversity (as a measure of variance) and total nonredundant information

(as a measure of volume) is important. Although having more samples of alters' topic space per period increased the number of novel topics sampled and the total volume of novel information received, it did not change the variance of the distribution of topics from which recruiters were sampling. Recruiters who increased the bandwidth of their communication channels saw increases in the total amount of novel information they received, but not necessarily in diversity per unit of information. When maintenance costs are considered, this implies that actors must weigh the benefits of additional novel information against the costs of obtaining that information, which makes the functional form of the relationship between novel information and performance particularly salient—a relationship we discuss in more detail below.

Finally, as the overlap of alters' information topic spaces increased, network diversity was less useful for delivering more total nonredundant information (table 6, model 13). Perhaps surprisingly, greater information overlap in an ego network was associated with greater access to nonredundant information. Upon reflection, it is clear why this relationship is positive. As the topic spaces of alters grew larger, they were more likely to overlap, but they were also more likely to contain more total novel information and to thus offer more novel topics to ego. This is confirmed by the fact that when topic space was added to the specification in model 13, the information overlap variable did not significantly predict total nonredundant information.

In summary, network diversity and channel bandwidth both predict access to more diverse information and more total nonredundant information, although bandwidth is a more powerful predictor of the total volume of novel information received. As alters' topic spaces grew larger and changed more rapidly, bandwidth became more important for delivering novel information. Finally, the more alters' information overlapped, the less important network diversity became to delivering novel information.

Performance Effects

Table 7 displays strong evidence of a positive relationship between access to nonredundant information and performance, as measured by revenues generated per month, projects completed per month, and average project duration.[35] We estimated both random-effects and fixed-effects specifications, but in the interests of space provide only the more conservative

[35] As there are some employees who do not take on projects or who are not involved in any projects in a given month, we estimate equations only for individuals with nonzero revenues in a given month.

TABLE 7

PERFORMANCE EFFECTS OF NETWORK DIVERSITY, CHANNEL BANDWIDTH, AND NONREDUNDANT INFORMATION: FIXED-EFFECTS SPECIFICATIONS

	Dependent Variable: Project Duration			Dependent Variable: Projects Completed			Dependent Variable: Revenues Generated		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Network diversity ...	−16.02***	−14.15***	−12.28***	.037***	.02**	.01	802.2	365.44	−420.4
	(3.90)	(3.39)	(3.53)	(.010)	(.01)	(.01)	(520.15)	(544.69)	(479.47)
Bandwidth	−5.35	−2.41	−1.57	.023**	.002	−.01	1,585.3***	899.25*	544.47
	(2.92)	(4.22)	(4.05)	(.009)	(.01)	(.01)	(493.79)	(467.81)	(517.18)
NRI		−12.64***	−19.00***		.10***	.16***		2,947.46***	5,626.2***
		(4.72)	(5.19)		(.02)	(.02)		(617.80)	(933.27)
NRI squared			7.70***			−.07***			−6,858.8***
			(1.91)			(.01)			(1,545.01)
Constant	307.96***	305.04***	302.62***	.64***	.66***	.60***	27,865***	28,545***	27,447***
	(.287)	(1.17)	(2.74)	(.004)	(.004)	(.01)	(276.15)	(227.28)	(438.83)
Temporal controls ...	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year	Month/ year
F-value	1.8E6***	4.6E3***	4.3E3***	1.29E7***	1.4E5***	5.2E4***	1.78E6*	2.6E4**	3.2E4***
(*df*)	(11)	(12)	(13)	(11)	(12)	(14)	(11)	(12)	(13)
R^2	.08	.09	.10	.05	.08	.14	.05	.06	.10
N	416	416	416	416	416	416	416	416	416

* $P < .10$.

** $P < .05$.

*** $P < .01$.

fixed-effects results here. Random-effects estimates were all in the same direction and were stronger than fixed-effects results.

As recruiters' structural diversity and channel bandwidth increased, they fulfilled contracts more quickly, fulfilled more contracts per unit of time, and generated more revenue.[36] A 1-SD increase in the bandwidth of communication channels was associated with just over $1,500 more revenues generated (per person per month; model 7, $P < .01$) and an additional two-tenths of a project completed (model 4, $P < .05$). The performance effects of network structure were enabled in large part by the provision of nonredundant information. When nonredundant information was added to the specifications, the performance effects of network structure were reduced and nonredundant information strongly predicted performance across all dimensions. A 1-SD increase in the amount of nonredundant information flowing to individuals was associated on average with just over $2,900 more in revenues generated (model 8, $P < .01$), an extra one-tenth of one project completed (model 5, $P < .01$), and an average project duration that is 12 days shorter per person per month (model 2, $P < .01$). These results offer evidence that diverse networks provide access to diverse, nonredundant information, which in turn predicts performance. As a robustness check, we estimated the relationships between information diversity (the variance measure) and performance with very similar results. A 1-SD increase in information diversity was associated with increases in revenues ($\beta_{FE} = 1{,}322.97$, NS; $\beta_{RE} = 2{,}254.75$, $P < .01$) and project completions ($\beta_{FE} = .036$, $P < .05$; $\beta_{RE} = .049$, $P < .01$) and with reductions in average project duration ($\beta_{FE} = -16.04$, $P < .01$; $\beta_{RE} = -15.78$, $P < .01$).

We also uncovered evidence of alternative mechanisms linking network structure to performance. With access to novel information held constant, network diversity was associated with more completed projects (model 5, $P < .05$) and faster project completion (models 2 and 3, $P < .01$). These results imply that benefits to network diversity come not just from access

[36] Given the core-periphery structure of the e-mail network of this firm (displayed in fig. 4), we compared the effects of network diversity on performance for those employees physically located at the headquarters with the effects for those who worked in peripheral offices. Our estimates of pooled OLS regressions provide evidence that being in a peripheral office is associated with lower performance and that the interaction effect of being in a peripheral office and having a diverse network is positive, implying the potential for network diversity to be even more important for the geographically isolated. We do not report these results in this article because of space and focus considerations and because estimated relationships are not robust to panel data procedures given that geographic isolation is a time-invariant binary characteristic. However, these results indicate that future work on the importance of network diversity for the geographically isolated may be fruitful.

to novel information but also from other mechanisms, such as better job support, more power, or organizational influence (Burt 1992).

Across the board, access to nonredundant information had diminishing marginal performance returns for each of our performance measures (models 3, 6, and 9). These parameter estimates suggest that the marginal performance impacts of novel information are lower when employees already have access to significant amounts of novel information. In fact, as the graphs in figure 9 demonstrate, there seem to be negative returns to more novel information beyond the normalized mean.[37] Such nonlinearities in the value of novel information likely arise for at least two reasons. First, beyond the threshold for decision relevance, new information adds no value. Second, employees reach the limits of their information-processing capacity as excess novelty becomes burdensome or distracting. These explanations are consistent with theories of bounded rationality, limited cognitive capacity, and information overload.

DISCUSSION

Structural theories of social capital and brokerage have developed to a significant extent around intuitions and anecdotal evidence about how information is likely to be distributed in networks and how different types of information are likely to accrue to individuals in different structural positions (Simmel [1922] 1955; Moreno 1940; Granovetter 1973; Baker 1990; Burt 1992, 2008; Padgett and Ansell 1993; Uzzi 1996, 1997; Hansen 1999, 2002; Podolny 2001; Reagans and Zuckerman 2001, 2008*a*, 2008*b*). However, the actual information flowing between individuals is rarely observed (Burt 2008), and we have lacked detailed dynamic theories of how social groups access, share, and distribute information under different network and environmental conditions.

This article develops a theory of how social actors gain access to novel information that accounts for how information stocks are distributed in a network as well as how information flows between contacts. Specifically, we propose that a trade-off exists between gathering novel information through more diverse network structure and gathering it through higher-bandwidth communication channels. As diversity and bandwidth counterbalance one another, it is difficult to increase both simultaneously. Structurally diverse networks tend to deliver information that exhibits more variation across channels because there tends to be information

[37] For novel information greater than the normalized mean, coefficients in revenue regressions are negative and significant ($\beta_{FE} = -3{,}340.33$, $P < .05$; $\beta_{RE} = -3{,}207.06$, $P < .05$), and in completed projects regressions are negative, though not significant ($\beta_{FE} = -.04$, NS; $\beta_{RE} = -.04$, NS).

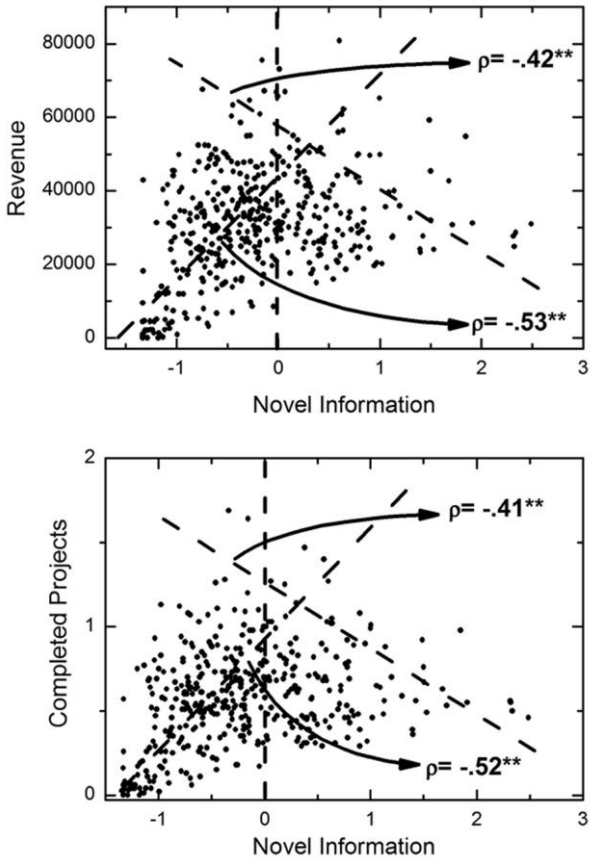

FIG. 9.—Graphs of the relationships between novel information, completed projects, and revenue.

homogeneity within connected social groups (Simmel [1922] 1955; Granovetter 1973; Blau 1986; Burt 1992). However, diverse networks also tend to include weaker ties (Granovetter 1973) that lack cooperative norms (Granovetter 1985; Coleman 1988) and display less multiplexity and dimensionality (Uzzi 1997; Hansen 1999), making them likely to deliver information on fewer topics with less accumulated novelty over time. We show—intuitively, analytically, and empirically—that this trade-off creates countervailing effects on access to novel information as measured by variance and by volume.

Statistical analyses that combine social network and performance data with direct observation of the information content flowing through e-mail

at a medium-sized executive recruiting firm provide strong evidence in support of the diversity-bandwidth trade-off. As network diversity increased, channel bandwidth fell, and both diversity and bandwidth delivered novel information. In accordance with existing theory, reaching across structural holes provides access to novel information. As recruiters communicated across structural holes, they tended to tap contacts with varied expertise and to receive more diverse information from them. However, they paid for this diversification by forgoing communication bandwidth that, all else equal, reduced the total volume of novel information they received through thicker bandwidth channels.

We also found support for each of the three main environmental conditions hypothesized to moderate the effects of the diversity-bandwidth trade-off: information overlap, topic space, and refresh rate. When contacts had redundant information, when they were aware of a larger number of topics, and when their information changed more rapidly, bandwidth was more influential in providing access to novel information. However, when recruiters' contacts had nonoverlapping information, when the topic space of ideas was smaller, and when updates were rarer, network diversity had a greater impact on access to novel information. These findings suggest that information benefits, vision advantages, and returns to brokerage are contingent on the information environments in which brokers find themselves. The prevailing wisdom among sociologists for the last 40 years has been that the strength of weak ties and information advantages to brokerage operate with a fair degree of regularity across contexts (Centola and Macy 2007). In contrast, our analysis shows that context matters. In certain information environments, brokers with many bridging ties to disparate parts of a social network can have *disadvantaged* access to novel information because their lower-bandwidth communication constrains the volume of novelty they receive.

High-bandwidth channels are more important in turbulent environments in which information changes rapidly. Several implications follow from this result. First, the prevailing view that information redundancy exists in dense cohesive networks ignores the fact that the information each actor has can be changing rapidly. A densely connected group of arbitrageurs in New York might all know each other well but may also constantly get new information from one another because what each person knows changes moment by moment. Second, weak, structurally diverse ties provide information at a lower rate, with less frequency, less complexity, and more delay. Weak ties are more likely to deliver obsolete information. In the classic case of job market opportunities or other time-sensitive settings such as stock market arbitrage, fewer relevant and useful opportunities are likely to arrive via diverse-low-bandwidth ties. The problem of stale information from remote ties is compounded by the fact

that our cohesive-high-bandwidth ties are more likely to know what we need and are therefore more likely to volunteer relevant information in a timely manner. Such thinking highlights the importance of timely access to novel information—rather than access alone—as a factor in brokerage theory.

The dependence of vision advantages on information turbulence suggests two important questions: which social environments are more turbulent, and is society moving toward greater overall information turbulence? The implications for brokerage are clear: if turbulence makes high-bandwidth channels relatively more important for access to novel information, then vision advantages from brokerage positions are less likely in social and economic sectors where the general stock of knowledge changes rapidly. If turbulence increases population heterogeneity, then diverse structure can remain salient. But if this is not the case and society is moving toward greater information turbulence, then over time brokerage positions could become less useful than leadership positions in cohesive cliques. Turbulent environments in which key environmental variables change quickly or a large number of new events occur within a given period of time have been described as postindustrial (Bell 1973; Huber 1984), high-velocity (Eisenhardt 1989), and time sensitive (Glazer and Weiss 1993) and are typically associated with markets in which information technology plays a critical role (Glazer 1991). Incorporating the rate of environmental change and information turbulence into brokerage theory could explain why brokerage is salient in some industries but not in others.

High-bandwidth channels also deliver more nonredundant information in high-dimensional information environments in which knowledge is complex and comprises many distinct topics. It is not surprising that evidence contradicting the predictions of brokerage theory typically emerges in R&D (Reagans and McEvily 2003), innovation (Obstfeld 2005), and the creative arts (Uzzi and Spiro 2005; Lingo and O'Mahony 2010). In these settings, novelty is produced by exploiting interactions among complex complementary ideas. In high-dimensional information environments, innovation is born of union strategies that connect alters rather than disunion strategies that keep them apart. Prior work describes these effects as resulting from complex interactions, collaborations, and brainstorming, which are all more likely to occur in dense cohesive networks in which strong ties are prevalent. Our work provides an additional underlying mechanism supporting this argument: increasing the volume of novel information flowing among collaborators provides even greater support for innovation in high-dimensional information environments. In contrast, in environments in which efficiency is more important than innovation, weaker ties are sufficient. Having been asked to provide "the

one thing you would change to improve [the company's] supply chain management" in 2,000 characters or less, supply chain managers possessing networks rich in structural holes provided answers that were scored higher in peer evaluations (Burt 2004). We speculate that these contrasting results can be explained by the complexity, or lack of complexity, in the ideas being solicited in the different contexts. Simple good ideas come more easily to brokers bridging structural holes, but complex innovation that requires coordinating high-dimensional interdependent information comes more readily from high-bandwidth communication.

An important question raised by the benefit of bandwidth in high-dimensional information environments is whether it is more important to develop "thick bridges" or "wide bridges," where a thick bridge refers to a high-bandwidth tie to a socially distant community and a wide bridge refers to several reinforcing weak ties to a socially distant community. Centola and Macy (2007) contend that, because adoption of complex behaviors requires social affirmation and reinforcement, exposure from multiple different contacts is the key structural characteristic of bridges across structural holes that enables diffusion of complex contagions. But our results show that thick, high-bandwidth bridges are critical to the amount of complex novel information that traverses a tie. The open question is whether a bundle of several weak ties is the same as one strong tie of equal channel bandwidth, in both the types of information they deliver and their role in social reinforcement and affirmation. Is the width or rather the thickness of a bridge more important for the movement of complex, high-dimensional information? In effect, when does the insight gleaned from 15 minutes with one doctor equal that of one minute with 15? To answer these questions, the importance of social reinforcement through multiple weak ties and rich interactions through high-bandwidth ties must be considered simultaneously. It could be that social reinforcement depends not only on multiple exposures but also on the transfer of rich information from trusted sources, which happens less often over low-bandwidth channels. Social reinforcement from multiple casual acquaintances may be less important than social reinforcement from one trusted peer. High-bandwidth ties could therefore also explain the tendency of social movements to diffuse spatially (Centola and Macy 2007). Our results imply that the most important tie for access to high-dimensional novelty is the thick bridge—a high-bandwidth tie to a distant network neighborhood.

Finally, information-based mechanisms do in fact explain performance benefits to brokerage. Network structure explains access to novel information, which in turn explains variation in performance. These results confirm prior theory and represent some of the first quantitative evidence of an information-based mechanism explaining returns to brokerage. As

recruiters accessed more diverse information (variance) and more total nonredundant information (volume), they generated more revenue, completed more projects per unit of time, and completed projects faster. These results held even in conservative fixed-effects specifications and were stronger in random-effects models that also evaluated variation across recruiters. An important limitation is that we cannot make causal claims about the relationship between access to information and performance (Aral, Muchnik, and Sundararajan 2009; Aral 2011; Aral and Walker, in press). In order to identify these relationships, future work could exploit random exogenous variation in the receipt of novel information to examine whether access to information actually causes performance increases or whether top performers are simply magnets for information. More detailed theoretical development and new empirical inquiry in different contexts will no doubt shed further light on these and other trade-offs. Toward this end, our methods for analyzing network structure and information content in e-mail data are replicable, opening a new line of inquiry into the information mechanisms that make social networks valuable.

CONCLUSION

The importance of weak ties and sparse networks is that they connect individuals to socially distant ideas and novel information. Access to novel information provides vision advantages to individuals that connect socially distant network neighborhoods. These two inferences have for decades guided sociologists' thinking on information flow in networks. However, our research shows that as networks become more structurally diverse, the volume of information flowing between dyads falls; that is, channel bandwidth contracts. This trade-off between network diversity and channel bandwidth regulates the degree to which structurally diverse networks deliver nonredundant information to actors in brokerage positions. As individuals communicate across structural holes, they tend to tap contacts with varied expertise and to receive more diverse information from them. However, they pay for that diversification by forgoing communication bandwidth, which on balance reduces the total volume of novel information they receive over time. Novelty must be measured in terms of information variety and information volume, and both are affected by the diversity-bandwidth trade-off. In turbulent and high-dimensional information environments, this trade-off implies that brokers with bridging ties to disparate parts of a social network can actually have *disadvantaged* access to novel information because their lower-bandwidth communication curbs the total volume of received novelty. Our findings

therefore suggest that information advantages to brokerage are contingent on the information environments in which brokers find themselves.

APPENDIX A

Models of the Diversity-Bandwidth Trade-off: Proofs of Consequences for Information Acquisition

To make our claims precise regarding the diversity-bandwidth trade-off, this appendix provides probabilistic models of information acquisition. Such models also address the "prior knowledge" problem. In a deterministic model, a person needs to know who knows what exactly in order to ask for it. In a probabilistic model, a person needs to know only the best expected contact policy over the population without having to know which person knows what. This represents an even softer constraint than one imposed by a "transactive memory" model in which ego needs to know which alter to ask. Yet, bandwidth to a cohesive tie can be favored over weak access to a diverse tie. More generally, these models demonstrate when a constrained-high-bandwidth tie can be expected to provide greater novelty than a diverse-low-bandwidth tie, and vice versa. Obviously, a diverse (unconstrained) high-bandwidth tie is best, but we wish to show how various degrees of constraint affect the diversity-bandwidth trade-off. The analysis proceeds in three parts, one each for topic space, information overlap, and refresh rate as shown in figure 2. Topic space is simplest, so we first generalize panel 4. "Biasing information overlap" generalizes panels 1–3. Finally, temporal analysis generalizes panels 5 and 6.

Without loss of generality, normalize the capacity of the low-bandwidth channel to 1 and that of the high-bandwidth channel to $B > 1$. Normalizing panel 1 in figure 2 illustrates a case in which the weak tie has bandwidth 1 and the strong tie therefore has proportional bandwidth 1.5.

Topic Space

Consider two diverse-low-bandwidth ties, with completely nonoverlapping information, and two constrained-high-bandwidth ties, with complete overlap.

PROPOSITION 1.—*As the number of available topics T grows without bound, constrained-high-bandwidth ties provide strictly greater expected novelty than diverse-low-bandwidth ties.*

Proof. Two nonoverlapping low-bandwidth ties provide two normalized units of novel information. Novelty on the first high-bandwidth channel is B. Complete overlap on the second high-bandwidth channel implies that only $T - B$ previously unshared items remain. Without repeating

herself (i.e., without replacement), the second high-bandwidth contact has the potential to reveal new items according to a hypergeometric distribution with draw capacity B. From standard probability theory, the mean of a hypergeometric distribution is $B(T - B)/T$ or simply $B - B^2/T$. Total expected novelty across two high-bandwidth channels is thus $2B - B^2/T$, which has limit $2B$ as T grows without bound. Since $2 < 2B$ for $B > 1$, this proves the claim. QED

As an aside, equation $2B - B^2/T$ implies that optimal bandwidth across both ties is T.

Information Overlap

To generalize insights concerning information overlap from panels 1–3, we introduce more flexible notation for information sharing "bias." Let there be $1, \ldots, n_i$ topics in in-group topic set n_i and $1, \ldots, n_o$ topics in out-group topic set n_o for a total of $n_i + n_o = T$. Define the likelihoods of encountering n_i and n_o topics as p_i and p_o, respectively. It follows that $n_i p_i + n_o p_o = 1$. An actor receives "biased" content if she is more likely to receive news on one set of topics than on another ($p_i > p_o > 0$), which we use to characterize the increased likelihood that cohesive high-bandwidth ties discuss the same things. Receiving completely *un*biased content is $p_i = p_o = 1/T$, whereas completely biased content $p_i = 1/n_i > p_o = 0$ or is $p_i = 0 < p_o = 1/n_o$. If ideas in n_i become x times more likely to appear among in-group communications, then $p_i = x/T$ (which implies that $p_o = [1 - n_1(x/T)]/(T - n_1)$ with $n_i < T$, $x < T$, and $xn_i \leq T$).

With this terminology, we can derive $P(\Psi_{\text{biased}})$, the probability of encountering a new idea given that there are k ideas remaining to be seen, allowing differences in p_i and p_o. Let E represent the event that a person encounters new information through a new link. Since novelty depends on what one has learned from prior links, let L represent links. Then, define the following:

$$I_{lk} = \begin{cases} 1 & \text{if } l \text{ connects to idea } k \\ 0 & \text{otherwise,} \end{cases}$$

$$J_k = \begin{cases} 1 & \text{if } \sum_{l=1}^{L} I_{lk} = 0 \\ 0 & \text{otherwise,} \end{cases}$$

$$\Psi = \{\text{event that link } L + 1 \text{ connects to a new idea}\}.$$

Here J_k indicates whether idea k has failed to appear among the infor-

mation provided by any of the social links 1, . . ., L. Then $P(\Psi)$ can be constructed as follows:

$$\begin{aligned} P(\Psi) &= E[P(\Psi|J_1, \ldots, J_k)] \\ &= E\left[\sum_{l=1}^{n_i} J_l p_i + \sum_{h=n_1+1}^{T} J_h p_o\right] \\ &= n_i p_i E[J_l] + n_o p_o E[J_h] \\ &= n_i p_i (1 - p_i)^L + n_o p_o (1 - p_o)^L. \end{aligned} \tag{A1}$$

The last step arises because an idea that occurs with probability p must not have occurred in any of the previous L draws. It is useful to note three properties of $P(\Psi_{\text{biased}})$. First, unbiased information implies $p_i = p_o = 1/T$. Because unbiased ties provide equal access across all topics, unbiased chances of encountering a new idea simplify to $P(\Psi_{\text{unbiased}}) = (1 - 1/T)^L$. Second, having no prior links $L = 0$ implies that a new idea is encountered with certainty. Third, increasing links without bound, $L \to \infty$, implies that the chances of encountering a new idea approach zero. The likelihood of encountering novel information (for both biased and unbiased ties) decreases strictly and asymptotically toward zero with each additional tie L. This theoretical model exactly mirrors the pattern we observe empirically as shown in panel 2 of figure 8.

PROPOSITION 2.—*When the advantage of bandwidth swamps the disadvantage of bias, an ego prefers the constrained-high-bandwidth tie to the diverse-low-bandwidth tie to increase the chances of encountering novel information.*

PROPOSITION 3.—*When the disadvantage of bias swamps the advantage of bandwidth, an ego prefers the diverse-low-bandwidth tie to the constrained-high-bandwidth tie to increase the chances of encountering novel information.*

Proof. Let $P[E^c] = P(\Psi_{\text{biased}})$ and $P[E^D] = P(\Psi_{\text{unbiased}})$, where E^c and E^D represent the events of forging a constrained and a diverse link and getting new information with a single unit of bandwidth. To model the more frequent communication of the higher-bandwidth tie, let B represent additional chances to cover new material over the constrained link during a given interval. Simplifying, allow $n_o = T - n_i$.

To see that a constrained-strong tie could offer more novel information, let $p_i = p_o + \varepsilon$, implying negligible bias so that $P[E^c] \approx P[E^D]$. Then choose any B large enough such that the following inequality is strict:

$$\begin{aligned} P[E_L^c] + P[E_{L+1}^c] + \cdots + P[E_{L+B}^c] \approx P[E_L^D] + P[E_{L+1}^D] + \cdots \\ + P[E_{L+B}^D] > P[E_L^D]. \end{aligned} \tag{A2}$$

This demonstrates the first claim that a constrained-high-bandwidth tie can supply a greater volume of novel information than a diverse-low-bandwidth tie provides. To see when a diverse-low-bandwidth tie could be preferred, consider when extreme bias results in topic heterogeneity. The subset of n_i topics occurs with probability $p_i = B/T$ (such bias necessarily constrains $p_o \approx \varepsilon$). For ease of simplification, let $n_i = T/B$. Then algebra reduces relative probabilities to

$$P[E_L^c] = \left(1 - \frac{B}{T}\right)^L < \left(1 - \frac{1}{T}\right)^L = P[E_L^D]. \tag{A3}$$

This alternative case demonstrates the counterclaim that a diverse-low-bandwidth tie can supply a greater volume of novel information than a constrained-high-bandwidth tie provides. Although $P[E_L^C] = P[E_L^c] + \cdots + P[E_{L+B}^c]$ and increasing B adds more terms to $P[E_L^C]$ and none to $P[E_L^D]$, it also causes each term to approach zero faster. No matter how large the bandwidth of constrained ties, there always exists a fixed number of links L such that link $L + 1$ should be an unconstrained tie. This establishes the second claim. QED

While a range of intermediate cases span these two extremes, conditions exist when a person will always prefer one or the other type of link depending on bias, bandwidth, and the number of links already present.

Refresh Rate

To model information renewal, we consider a standard Poisson process. Let mn be the average time between samples in a subset of n topics and r be the average time until news is refreshed (see fig. A1).

The chance that a given sample produces new information is the ratio of average time between samples over the total time until information renews $mn/(mn + r)$. Note also that if m is average time between samples, then $1/m$ gives the number of samples per unit of time. Consider non-overlapping in-group and out-group topic subsets n_i and n_o with shorter sampling times for the higher-bandwidth in-group.

PROPOSITION 4.—*Let high-bandwidth ties provide more frequent updates, $m_i < m_o$ (so sample times are shorter), but let low-bandwidth ties provide access to distinct topics n_o not included in n_i. Then among ties balanced to provide optimal access to news, an increase in the refresh rate favors an increase in high-bandwidth ties.*

Proof. We first find the optimal balance between in-group and out-group ties and then show that the proportion of in-group ties grows in refresh rate. Since the number of ties is finite, the sum of samples per unit of time is bounded by the number of social links $1/m_i + 1/m_o \leq L$. To get the most news, a person chooses

$$\max \pi = (\text{In-Group Samples}) \times P(\text{In-Group Success}) + (\text{Out-Group Samples}) \times P(\text{Out-Group Success}),$$

$$\max_{m_i, m_o} \pi = \frac{1}{m_i}\left(\frac{m_i n_i}{m_i n_i + r_i}\right) + \frac{1}{m_o}\left(\frac{m_o n_o}{m_o n_o + r_o}\right)$$

such that $1/m_i + 1/m_o \leq L$.

Use boundary condition $1/m_o = L - 1/m_i$ to substitute for m_o. Since refresh occurs sooner in higher-bandwidth ties, substitute for out-group refresh rate using $r_o = \delta r_i$, $\delta \geq 1$. Solving $\partial\pi/\partial m_i = 0$ produces a quadratic equation with two roots, of which the second is out of bounds:

$$\frac{1}{m_i} = \left\{\frac{L\delta n_i}{n_o + \delta n_i}, \; -\frac{n_i(2n_o + \delta L r_i)}{(n_o - \delta n_i) r_i}\right\}.$$

On the basis of the first root, the absolute time to spend on in-group ties rises in the number of ties L, the relative refresh delay on out-group topics δ, and the number of in-group topics n_i. It falls in the number of out-group topics n_o. The *proportion* of time to spend on high-bandwidth ties is

$$\frac{1/m_i}{1/m_i + 1/m_o} = \frac{\delta n_i}{n_o + \delta n_i},$$

which increases strictly toward one as the refresh delay of out-group topics increases. Higher refresh rates strictly favor a higher proportion of high-bandwidth ties. QED

APPENDIX B

Descriptions and Correlations of Information Diversity Metrics

Table B1 presents the correlations of the following five measures of information diversity.

TABLE B1
CORRELATIONS BETWEEN THE FIVE MEASURES OF INFORMATION DIVERSITY

Measure	1	2	3	4	5
1. InfoDiversity	1.0000				
2. VarDiceSim	.9999	1.0000			
3. AvgCommon	.9855	.9845	1.0000		
4. AvgCommonIC	.9943	.9937	.9973	1.0000	
5. AvgClusterDist	.9790	.9778	.9993	.9939	1.0000

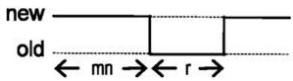

FIG. A1

Information Diversity (ID)

Variance based on cosine distance (cosine similarity):

$$ID_i^I = \frac{\sum_{j=1}^{N} [1 - \cos(d_{ij}^I, M_i^I)]^2}{N},$$

where

$$\cos(d_{ij}, M) = \frac{d_i \cdot M_i}{|d_i||M_i|} = \frac{\sum_j w_{ij} \times w_{Mj}}{\sqrt{\sum w_{ij}^2}\sqrt{\sum w_{Mj}^2}}.$$

We measure the variance of deviation of e-mail topic vectors from the mean topics vector and average the deviation across e-mails in a given in-box or out-box. The distance measurement is derived from a well-known document similarity measure—the cosine similarity of two topic vectors.

Dice's Coefficient Variance

Variance based on Dice's distance and Dice's coefficient:

$$\text{var Dice}_t^I = \frac{\sum_{j=1}^{N} [\text{DistDice}(d_{ij}^I)]^2}{N},$$

where

$$\text{DistDice}(d) = \text{DiceDist}(d, M) = 1 - \text{Dice}(d, M),$$

and where

$$\text{Dice}(D_1, D_2) = \frac{2\sum_{i=1}^{T} (t_{D_{1j}} \times t_{D_{2j}})}{\sum_{i=1}^{T} t_{D_{1j}} + \sum_{i=1}^{T} t_{D_{2j}}}.$$

Similar to var cos, variance is used to reflect the deviation of the topic vectors from the mean topic vector. Dice's coefficient is used as an alternative measure of the similarity of two e-mail topic vectors.

Average Common Cluster

AvgCommon measures the level to which the documents in the document set reside in different k-means clusters produced by the eClassifier algorithm:

$$\text{AvgCommon}_i^I = \frac{\sum_{j=1}^{N} [\text{CommonDist}(d_{1j}^I,\ d_{2j}^I)]}{N},$$

where $(d_{1j}^I,\ d_{2j}^I)$ represents a given pair of documents (1 and 2) in an in-box and j indexes all pairs of documents in an in-box, and where

$$\text{CommonDist}(d_{1j}^I,\ d_{2j}^I) = 1 - \text{CommonSim}(d_{1j}^I,\ d_{2j}^I),$$

$$\text{CommonSim}(d_{1j}^I,\ d_{2j}^I) = \frac{\sum \text{Iterations in same cluster}}{\sum \text{Iterations}}.$$

AvgCommon is derived from the concept that documents are similar if they are clustered together by k-means clustering and dissimilar if they are not clustered together. The k-means clustering procedure is repeated several times, creating several clustering results with 5, 10, 20, 30, 40, . . . , 200 clusters. This measure counts the number of times during this iterative process two e-mails were clustered together divided by the number of clustering iterations. Therefore, every two e-mails in an in-box and out-box that are placed in separate clusters contribute to higher diversity values.

Average Common Cluster with Information Content

AvgCommonIC uses a measure of the "information content" of a cluster to weight in which different e-mails reside. AvgCommonIC extends the AvgCommon concept by compensating for the different amount of information provided in the fact that an e-mail resides in the same bucket for either highly diverse or tightly clustered clusters. For example, the fact that two e-mails are both in a cluster with low intracluster diversity is likely to imply more similarity between the two e-mails than the fact that two e-mails reside in a cluster with high intracluster diversity:

$$\text{CommonICSim}(D_1,\ D_2) = \frac{1}{\log(1/\|\text{all documents}\|)} \cdot \frac{\sum_{D_1, D_2 \text{in same bucket}} \log(\|\text{documents in the bucket}\|/\|\text{all documents}\|}{\text{total number of bucket levels}},$$

$$\text{CommonICDist}(D_1,\ D_2) = 1 - \text{CommonICSim}(D_1,\ D_2),$$

$$\text{AvgCommonIC} = \text{average}_{d_1, d_2 \in \text{documents}}\{\text{CommonICDist}(d_1,\ d_2)\}.$$

Average Cluster Distance

AvgBucDiff measures diversity using the similarity/distance between the clusters that contain the e-mails:

$$\text{AvgBucDiff} = \text{average}_{d_1, d_2 \in \text{documents}}\{\text{DocBucDist}(d_1, d_2)\},$$

where

$$\text{DocBucketDist}(D_1, D_2) = \frac{1}{\|\text{cluster iterations}\|} \cdot \sum_{i \in \text{cluster iterations}} [\text{BucketDist}(B_{\text{iteration} = i, D_2})],$$

and

$$\text{BucketDist}(B_1, B_2) = \cos \text{Dist}(m_{B_1}, m_{B_2}).$$

AvgBucDiff extends the concept of AvgCommon by using the similarity/distance between clusters. While AvgCommon differentiates only whether two e-mails are in the same cluster, AvgBucDiff also considers the distance between the clusters that contain the e-mails.

APPENDIX C

External Validation of Diversity Measures

We validated our diversity measurement using an independent, publicly available corpus of documents from Wikipedia.org. Wikipedia.org, the user-created online encyclopedia, stores entries according to a hierarchy of topics representing successively fine-grained classifications. For example, the page describing "genetic algorithms" is assigned to the "Genetic Algorithms" category, found under "Evolutionary Algorithms," "Machine Learning," "Artificial Intelligence," and subsequently under "Technology and Applied Sciences." This hierarchical structure enables us to construct clusters of entries on diverse and focused subjects and to test whether our diversity measurement can successfully characterize diverse and focused clusters accurately.

We created a range of high- to low-diversity clusters of Wikipedia entries by selecting entries either from the same subcategory in the topic hierarchy to create focused clusters or from a diverse set of unrelated subtopics to create diverse clusters. For example, we created a minimum diversity cluster (type 0) using a fixed number of documents from the same third-level subcategory of the topic hierarchy and a maximum diversity cluster (type 9) using documents from unrelated third-level subcategories. We then constructed a series of document clusters (type 0 to type 9) ranging from low to high topic diversity from 291 individual entries

as shown in figure C1.[38] The topic hierarchy from which documents were selected appears in table C1.

If our measurement is robust, our diversity measures should identify type 0 clusters as the least diverse and type 9 clusters as the most diverse. We expect that diversity will increase relatively monotonically from type 0 to type 9 clusters, although there could be debate, for example, about whether type 4 clusters are more diverse than type 3 clusters.[39] After creating this independent data set, we used the Wikipedia entries to generate keywords and measure diversity using the methods described above. Our methods were very successful in characterizing diversity and ranking clusters from low to high diversity. Figure C2 displays cosine similarity metrics for type 0 to type 9 clusters using 30, 60, and 90 documents to populate clusters. All five diversity measures return increasing diversity scores for clusters selected from successively more diverse topics.[40] Overall, these results give us confidence in the ability of our diversity measurement to characterize the subject diversity of groups of text documents of varying sizes.

APPENDIX D

Model Specifications and Estimation Procedures

Model Specifications

To explore the mechanisms driving the creation and appropriation of information advantages from network structure, we first explicitly considered the trade-off between network diversity and channel bandwidth by estimating the two following specifications:

[38] We created several sets of clusters for each type and averaged diversity scores for clusters of like type. We repeated the process using three, six, and nine document samples per cluster type to control for the effects of the number of documents on diversity measures.

[39] Whether type 3 or type 4 clusters are more diverse depends on whether the similarity of two documents in the same third-level subcategory is greater or less than the difference of similarities between documents in the same second-level subcategory as compared to documents in categories from the first hierarchical layer onward. This is, to some extent, an empirical question.

[40] The measures produce remarkably consistent diversity scores for each cluster type, and the diversity scores increase relatively monotonically from type 0 to type 9 clusters. The diversity measures are not monotonically increasing for all successive sets, such as type 4, and it is likely that the information contained in type 4 clusters is less diverse than in type 3 clusters simply because two type 4 documents are taken from the same third-level subcategory.

TABLE C1
WIKIPEDIA.ORG CATEGORIES

+ Computer Science	+ Geography	+ Technology
+ Artificial intelligence	+ Climate	+ Robotics
+ Machine learning	+ Climate change	+ Robots
+ Natural language processing	+ History of climate	+ Robotics competitions
+ Computer vision	+ Climate forcing	+ Engineering
+ Cryptography	+ Cartography	+ Electrical engineering
+ Theory of cryptography	+ Maps	+ Bioengineering
+ Cryptographic algorithms	+ Atlases	+ Chemical engineering
+ Cryptographic protocols	+ Navigation	+Video and movie technology
+ Computer graphics	+ Exploration	+ Display technology
+ 3D computer graphics	+ Space exploration	+ Video codecs
+ Image processing	+ Exploration of Australia	+ Digital photography
+ Graphics cards		

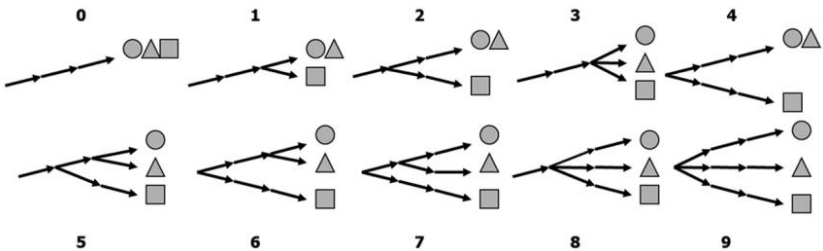

FIG. C2.—Document clusters selected from Wikipedia.org

$$B_{it} = \gamma_i + \beta_1 ND_{it} + \beta_2 SE_{it} + \beta_3 EH_{it} + \beta_4 NS_{it} + \beta_5 NS_{it}^2 + \sum_j \beta_j HC_{ji} + \sum_m \beta_m M_{it} + \varepsilon_{it}, \tag{D1}$$

$$ND_{it} = \gamma_i + \beta_1 SE_{it} + \beta_2 EH_{it} + \beta_3 NS_{it} + \beta_4 NS_{it}^2 + \beta_5 B_{it} + \sum_j \beta_j HC_{ji} + \sum_m \beta_m M_{it} + \varepsilon_{it}, \tag{D2}$$

where B_{it} represents channel bandwidth, ND_{it} represents network diversity (measured by one minus constraint), SE_{it} represents average structural equivalence, EH_{it} represents the knowledge heterogeneity of i's contacts, NS_{it} represents the size of i's network, NS_{it}^2 represents network size squared, $\sum_j \beta_j HC_{ji}$ represents controls for human capital and demographic variables (age, gender, education, industry experience, and managerial level), and $\sum_m \beta_m M_{it}$ represents temporal controls for each month/year. If network diversity and channel bandwidth trade off, network diversity should be associated with lower channel bandwidth, and we would expect

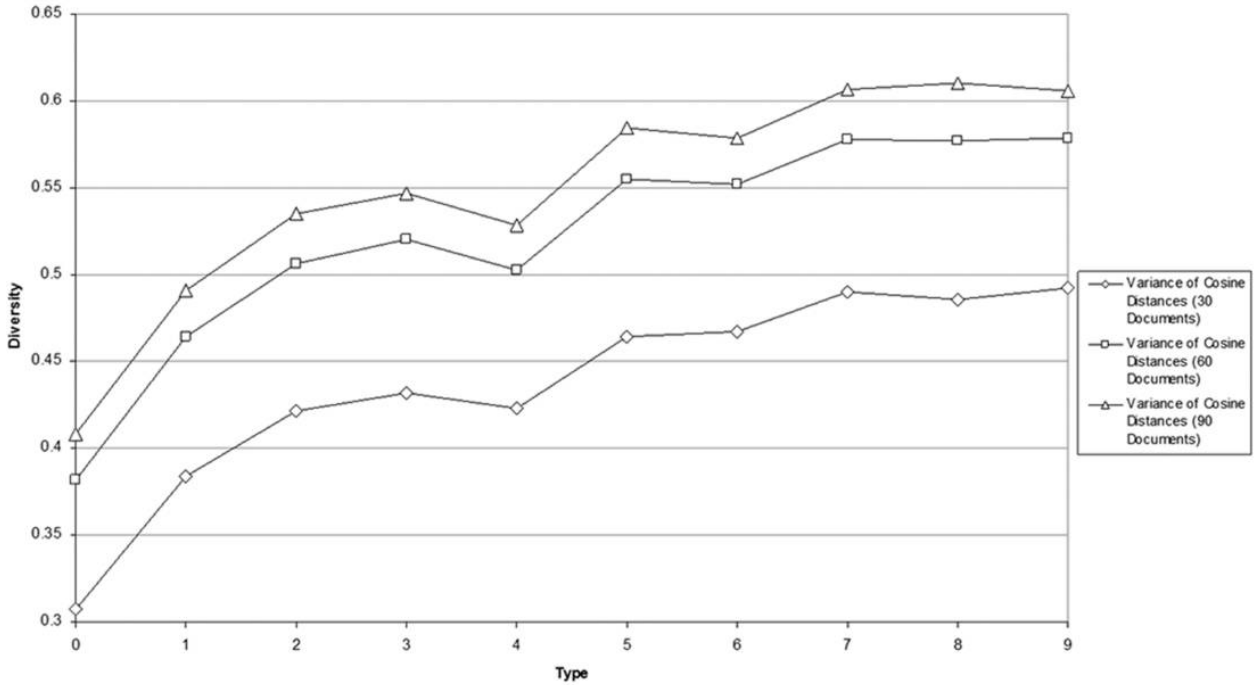

FIG. C1.—Diversity measurement validation results

to observe parameter estimates such that $\beta_1 < 0$ and $\beta_2 > 0$ in equation (D1) and $\beta_5 < 0$ in equation (D2).

We then examined the structural correlates of access to diverse and novel information. We first estimated an equation relating network structure to the diversity of information flowing into actors' e-mail in-boxes.[41] The estimating equation is specified as follows:

$$\begin{aligned} ID_{it}^{I} = {} & \gamma_i + \beta_1 E_{it}^{I} + \beta_2 EH_{it} + \beta_3 ND_{it} + \beta_4 SE_{it} + \beta_5 NS_{it} + \beta_6 NS_{it}^2 \\ & + \beta_7 B_{it} + \beta_8 R_{it} + \beta_9 (B_{it} \times R_{it}) + \beta_{10} TS_{it} + \beta_{11} (B_{it} \times TS_{it}) \\ & + \beta_{12} IO_{it} + \beta_{13} (ND_{it} \times IO_{it}) + \sum_j \beta_j HC_{ji} + \sum_m \beta_m M_{it} + \varepsilon_{it}, \end{aligned} \tag{D3}$$

where ID_{it}^{I} represents the diversity of the information in a given individual's in-box, E_{it}^{I} represents the total number of incoming messages received by i, R_{it} represents the refresh rate of i's alters at time t, TS_{it} represents the topic space of i's alters at time t, and IO_{it} represents the information overlap of i's alters at time t. We then examined the relationship between network structure and the total amount of novel information flowing into actors' e-mail in-boxes (NRI_{it}^{I}) using the following model:[42]

$$\begin{aligned} \mathrm{NRI}_{it}^{I} = {} & \gamma_i + \beta_1 EH_{it} + \beta_2 ND_{it} + \beta_3 SE_{it} + \beta_4 NS_{it} + \beta_5 B_{it} \\ & + \beta_6 R_{it} + \beta_7 (B_{it} \times R_{it}) + \beta_8 TS_{it} + \beta_9 (B_{it} \times TS_{it}) \\ & + \beta_{10} IO_{it} + \beta_{11} (ND_{it} \times IO_{it}) + \sum_j \beta_j HC_{ji} + \sum_m \beta_m M_{it} + \varepsilon_{it}. \end{aligned} \tag{D4}$$

Finally, we tested the relationship between nonredundant information (NRI_{it}^{I}) and performance (P_{it}) and included our measures of network diversity (ND_{it}) and bandwidth (B_{it}) in the specification:

$$\begin{aligned} P_{it} = {} & \gamma_i + \beta_1 ND_{it} + \beta_2 B_{it} + \beta_3 \mathrm{NRI}_{it}^{I} + \beta_4 (\mathrm{NRI}_{it}^{I})^2 \\ & + \sum_j \beta_j HC_{ji} + \sum_m \beta_m \mathrm{Month} + \varepsilon_{it}. \end{aligned} \tag{D5}$$

If information benefits to network diversity and channel bandwidth exist, they should be positively associated with access to diverse and nonredundant information, and nonredundant information should be pos-

[41] We focus in this article on incoming information for two reasons. First, we expect network structure to influence incoming information more than outgoing information. Second, the theory we intend to test is about the information to which individuals have access as a result of their network structure, not the information individuals send. These dimensions are highly correlated.

[42] We did not include the network size squared term because it had no explanatory power. The relationship between network size and total nonredundant information is linear and positive.

itively associated with performance. If network structure confers additional benefits beyond information advantage (such as power or favorable trading conditions), network diversity and channel bandwidth should contribute to performance beyond their contribution through information diversity.[43] Finally, if there are diminishing returns to novel information, we should see a concave relationship between novel information and productivity. As a robustness check we also estimated equation (D5) replacing the nonredundant information variable (NRI^I_{it}) with incoming information diversity (ID^I_{it}) with similar results.

Estimation Procedures

We estimate relationships between network structure and information access and between information access and performance using panel data. We are interested in how variation in network structure explains performance differentials across individuals and also in how changes in actors' networks explain variation in their own performance over time. If network structure generates social capital by influencing information access, actors with larger, more diverse networks with higher channel bandwidth should receive more novel information and perform better than those with less diverse networks and lower channel bandwidth. However, evidence of variation across individuals cannot exclude the possibility that unobservable characteristics of individuals, such as ambition or social intelligence, could simultaneously drive variation in network diversity and performance. If unobserved characteristics of individuals are correlated with the error terms in our models, pooled OLS estimation will produce biased parameter estimates. We therefore examine variation within and across individuals over time using both fixed-effects and random-effects models to control for bias created by this unobserved heterogeneity and to examine variation within and across observations of individuals over time.

The fixed-effects estimator uses variation within observations of a single individual over time. The basic specification includes observations of dependent and independent variables for each individual in each cross-sectional time period t and a time-invariant vector of individual characteristics α_i representing unobserved heterogeneity across individuals:

[43] We were unable to reject the hypothesis of no heteroscedasticity and report standard errors according to the White correction (White 1980). White's approach is conservative. Estimated coefficients are unbiased but not efficient. In small samples, we may observe low t-statistics even when variables exert a real influence. As there may be idiosyncratic error at the level of individuals, for OLS analyses we report robust standard errors clustered by individual. Clustered robust standard errors are robust to correlations within observations of each individual but are never fully efficient. They are conservative estimates of standard errors.

$$y_{it} = \alpha_i + x_{it}\beta + \varepsilon_{it}. \tag{D6}$$

The fixed-effects transformation is obtained by first averaging equation (D6) over $t = 1, \ldots, T$ to create the cross-section equation or between estimator:

$$\bar{y}_i = \alpha_i + \bar{x}_i\beta + \bar{\varepsilon}_i, \tag{D7}$$

where

$$\bar{y}_i = \frac{\sum_1^T y_{it}}{T}, \quad \bar{x}_i = \frac{\sum_1^T x_{it}}{T}, \quad \text{and } \bar{\varepsilon}_i = \frac{\sum_1^T \varepsilon_{it}}{T}.$$

When we subtract equation (D7) from equation (D6), the fixed-effects transformation removes unobserved time-invariant individual-specific heterogeneity embodied in α_i:

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)\beta + \varepsilon_{it} - \bar{\varepsilon}_i. \tag{D8}$$

The fixed-effects estimator produces estimates using variation within observations of the same individuals over time and allows us to estimate the effects of network structure controlling for unobserved omitted variables that could bias our estimates.

While the fixed-effects estimator helps us estimate the effects of network structure on information access and performance controlling for unobservable omitted variables, it has several drawbacks. First, we are also interested in the effects of observable time-invariant characteristics of individuals, such as demography (e.g., age, gender), human capital (e.g., education, industry tenure), and organizational hierarchy (e.g., individuals' position in the firm's formal organizational structure), on access to information and performance. More precisely, we are interested in the relative effects of network structure on information access and performance compared to these traditional factors. As the fixed-effects estimator washes away variation in time-invariant characteristics, it makes estimation of these parameters impossible. Second, we believe that variation across individuals also helps explain differences in information access and performance correlated with network structure. Individuals may be able to manipulate the information they receive by changing their communication patterns over time, but persistent structural differences between individuals could also explain performance differentials. We therefore estimate both pooled OLS and random-effects models of our specifications as robustness checks with similar results.

The OLS estimator on pooled data estimates an unweighted average of the within and between estimators. Although we do not report these results in the tables, we produced pooled OLS estimates of our specifications with very similar results, which most closely resembled the random-effects estimates we report. We estimated the pooled OLS spec-

ifications with robust clustered standard errors in order to control for the fact that repeated observations of the same individuals over time in panel data may artificially constrict the standard errors. Clustered robust standard errors treat each individual as a super-observation for part of its contribution to the variance estimate (e.g., $\varepsilon_{ci} = \eta_c + \upsilon_{ci}$, where η_c is an individual effect and υ_{ci} the idiosyncratic error). They are robust to correlations within the observations of each individual but are never fully efficient. They represent conservative estimates of standard errors.

When variables of interest do not vary much over time, fixed-effects methods can produce imprecise estimates. In our case, not only are we interested in estimating the impact of time-invariant characteristics of individuals on access to information and performance (e.g., age, gender, education), but we also know that certain aspects of network structure change relatively little over time. We therefore estimate both fixed-effects and random-effects specifications. The random-effects model estimates a matrix weighted average of the between (D7) and within (D8) estimators, where the weighting matrix λ accounts for correlation across observations in the residuals as follows:

$$y_{it} - \overline{\lambda y_i} = (x_{it} - \overline{\lambda x_i})\beta + \varepsilon_{it} - \overline{\lambda \varepsilon_i}. \tag{D9}$$

We estimate λ as a function of the idiosyncratic error variance and the group-specific error variance. When $\lambda = 0$, the procedure is equivalent to estimating OLS, and when $\lambda = 1$, we are estimating fixed effects. The random-effects model brings efficiency gains and the ability to estimate parameters of time-invariant covariates at the risk of inconsistency. To test the consistency of the random-effects estimator, we conduct Hausman tests (Hausman 1978) comparing fixed- and random-effects models and report our results in the table notes for each set of results.

To adjust for nonindependence of observations in network panel data, we employ a consistent covariance matrix estimator that is robust to very general forms of network, spatial, and temporal dependence (Driscoll and Kraay 1998). This approach is similar to common network autocorrelation models considered in the literature (e.g., Ord 1975; Doreian 1980; Dow, Burton, and White 1982; Loftin and Ward 1983; Marsden and Friedkin 1993) but also takes into account temporal dependence across panels in longitudinal data as well as both cross-sectional and time-dependent network autocorrelation. The estimator assumes a data-generating process with both contemporaneous and lagged cross-sectional dependence across observations as follows:

$$y_{it} = x_{it}\beta + \varepsilon_{it}, \tag{D10}$$

where

$$\varepsilon_{it} = \lambda_i f_t + \nu_{it},$$

and

$$f_t = \rho f_{t-1} + u_{it},$$

where u_{it} and ν_{it} are mutually independent normal random variables with mean zero, and contemporaneous and lagged cross-sectional dependence in disturbances is modeled through the presence of the unobserved factor f_t. The extent of dependence between two observations i and j depends on the strength of the network autocorrelation terms λ_i and λ_j and the degree of temporal persistence in the factor ρ.

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